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Reducing the Cost of Operational Water on Military Bases Through Modeling, Optimization, and Control

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Reducing the Cost of Operational Water on Military Bases Through Modeling, Optimization, and Control

by

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Dedicated to my sons. May they also take on challenges that seem insurmountable.

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Reducing the Cost of Operational Water on Military Bases Through Modeling, Optimization, and Control

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Military municipal water systems provide safe and clean water to the surrounding community while also supporting the intense and often unpredictable training schedules of the tenant units. Much like their civilian counterparts, military water systems are also consumers of great amounts of energy and capital. As a part of the Army Net Zero program in 2011, an annual water inventory conducted on eight U.S. Army installations concluded that consumption was 5.5 billion gallons. Using the Environmental Protection Agency's average national estimate of 1,500 kWh of energy consumed for every 1,000 gallons of treated water, it is readily apparent that the department of defense is a heavy consumer of both water and energy. Because the scale of the military's usage is so vast, so too is their waste. Waste in water systems is common and commonly neglected, as many were initially constructed decades ago and the commodity that they transport is relatively inexpensive. However, recent droughts affecting regions of the United States highlighted the need to conserve and avoid waste, regardless of the commodity price. The efficiency of water systems is highly dependent upon developing accurate models and using those models to accurately deal with disturbances such as demand and chlorine concentration. This work extends water distribution system modeling, optimization, and control to a military setting where constraints are tighter for resiliency purposes, demands are often unpredictable, and saving money and water improves defense capabilities. First, a discretized nonlinear, equation based model of a known system at an existing U.S. Army installation that accurately predicts system behavior under typical demand considerations. The model is calibrated for accuracy using actual system data from a military installation and employed in a nonlinear optimization program to study reduction of costs, minimizing waste, and improvements in energy efficiency. Demand profiles were constructed from residential data and scaled to better represent demand on military bases. With very little adjustment, this model can be used to optimize similar systems in the military inventory. Water and energy savings exceed 10% in the optimized system, which predicts the Army could save greater than \$1.5 million per year in the continental United States if rigorous optimization was conducted on storage and pumping at every base. It is shown that a reduced order empirical model is a viable alternative to the computationally expensive equation based approach. The empirical model is used to implement model predictive control, providing the system protection against large and unpredictable disturbances. This method adds an additional manipulated variable, chlorine injection, to ensure efficient constraint compliance. Experimental results show this method further supports the aforementioned savings in the optimized system alone, while efficiently handling

disturbances.

This research closes previous gaps in research, particularly on military installations. First, it serves to minimize the system volume, or excess water on hand, while meeting all demands and strict system constraints dictated by resiliency and emergency preparedness. Secondly, this work uses a nonlinear model predictive control structure to deal with large and unpredictable disturbances that occur uniquely on military installations. The feedforward control action integrated into the controller is particularly effective at minimizing disturbances on inlet concentration.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Motivation

The motivation for this work stems from the author's affection for the U.S. military, an organization he has dedicated his entire adult life to serving, a deep affection for the wonders of science and technology, and the sense that water resources management and protection will be a worldwide challenge for decades to come. Sometimes, large organizations–despite their success in other areas–are plagued by the inability to embrace new technology and organizational change. Resistance to change could be due to a variety of reasons: funding, lack of information, prioritization, or apathy. Although the military is innovative with respect to tactical water systems, it suffers from an innovation deficit in its municipal water systems. For the military to make progress in this critical area, they should consider the exciting technological innovations that drive potential efficiencies of water delivery systems while overcoming the political, cultural, and economic factors that hinder such progress [29]. In the military's case, institutional innovation will likely be of similar importance to technological progress when the military's water systems begin to make exponential progress.

1.2 Background

Water systems that provide potable water to residential, industrial, or military customers are inherently complex, where the network of pipes, tanks, valves, and reservoirs, along with competing constraints, limits on controlled variables, and unpredictable disturbances, create a need for optimization and control. The complexity of several interconnected process units in parallel with the chemistry of chlorine degradation require that the system operate at its maximum efficiency and produce minimal waste. According to the U.S. Environmental Protection Agency, over 76% of energy used in water systems is for pumping and storage [35]. Implementing rigorous optimization and control on water systems can reduce power consumption on military bases, but also reduce the excessive amounts of water currently treated and stored that exceeds demand. One viable approach to achieve optimal operational system efficiency and reduce cost is to develop a sufficiently accurate model of each individual sub-process within the system and then rigorously determine the system wide optimal operating parameters. Optimal conditions that reduce waste, energy, and capital are dependent upon several key factors such as the inlet concentration of chlorine, demand patterns, ambient temperature, and reaction chemistry within the system. These conditions are not constant, varying for all times as measured and unmeasured disturbances. Although existing sensor technology could provide sufficient measurement of critical system variables and allow the development of data-driven models for reducing the effect of system disturbances, water systems engage in these practices on a very limited basis. Funding for sensor technology and large scale data gathering, which would provide increased reliability, better decision making, and continuous updating of process models, is not typically available. Although they convey, treat, and store one of our most precious resources, typical water systems do not utilize sensor technology, optimization, or control and adjustments on manipulated variables(MV) are typically based on heuristics. Contrary to industrial processes where corporate revenues drive efficiency and innovation, water system capital investment and innovation lag behind simply because historical prices of water are relatively inexpensive (see Figure 1.1). Even in an environment of low cost water, the U.S. Army spent $76.2 million on water in fiscal year 2014 [26].

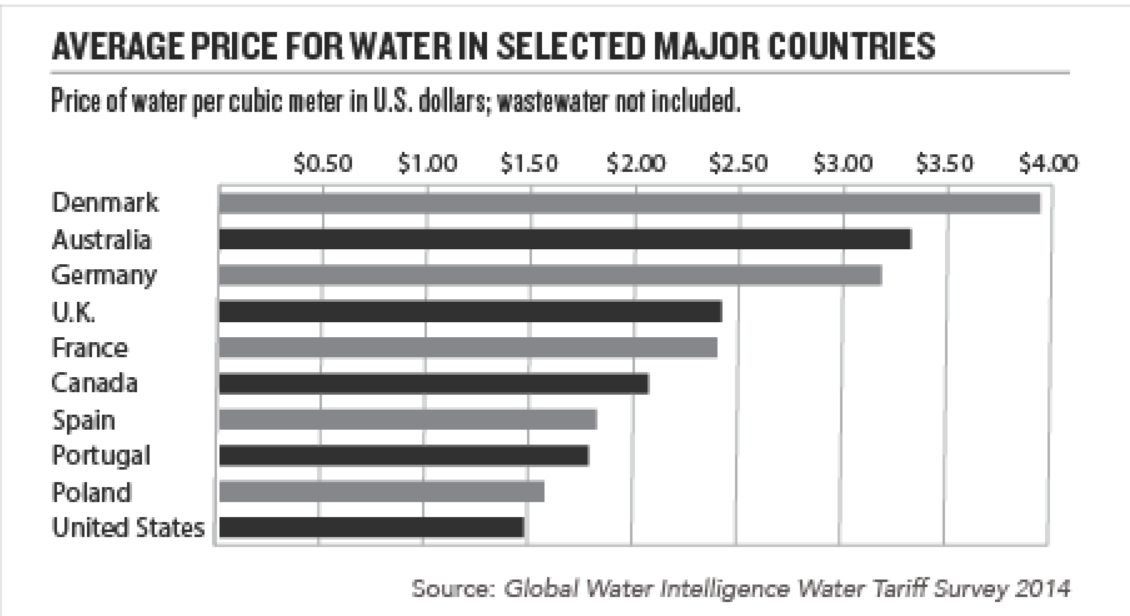

Figure 1.1: Price of water compared to customers in other developed countries worldwide, 2014. Water prices in the United States currently and historically rank among the least expensive worldwide.

Inexpensive water gave little incentive to modernize systems for efficiency until recently, when droughts, growing populations, and increasing demand from the petroleum industry across the United States highlighted just how scarce of a resource our water has become. Incentives to responsibly manage water are now based on stewardship, not necessarily cost.

The United States Department of Defense and the United States Army are becoming more proactive with respect to water and energy conservation, which gives them the opportunity for a leadership role in this critical area. During fiscal year 2014, the U.S. Army used 34.3 billion gallons of water to train and provide life support for service members and their families at installations within the continental United States(CONUS) [26]. Operating and training in a world where fresh water resources are less plentiful and appear to be rising in cost, the Army is taking measures to make water systems more efficient. Synonymous to the Department of Defense term *operational energy*, this work proposes that the term *operational water* should be defined as water required for training, moving and sustaining military forces and weapons platforms for military operations. The term includes water used by municipal and tactical water systems for life support, maintenance, medical and weapons platforms employed by military forces during training and in the field.

In 2010, the Army created the Net Zero Initiative, a deliberate campaign featuring eight of the Army's many installations to measure the effects of a renewed focus on efficiency and conservation. As part of the program, a water inventory was conducted at the eight Net Zero installations. As shown in Figure 1.2, the eight installations consumed approximately 5.5 billion gallons of water in the measured year. Of this amount, approximately 500 million gallons was due to system losses. System losses are defined in this work as water that is treated, conveyed and stored but never reaches the consumer due to inefficiencies in the system (not leaks). In summary, the military's consumption of potable water is substantial and they have plenty of room for improvements with respect to efficiency and waste. Positive improvements with respect to operational water will have a lasting impact on the budget, the environment, and the ability to fulfill the military's war fighting mission.

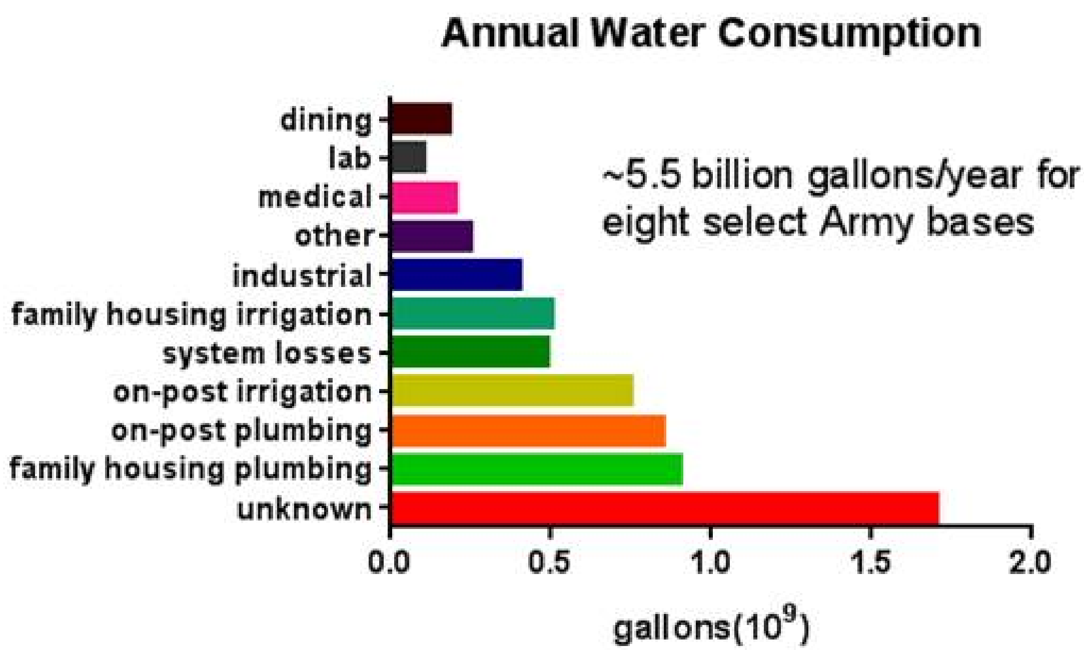

Figure 1.2: Annual water consumption for the eight bases involved in the United States Army Net Zero Initiative, as a result of a water inventory conducted to begin the initiative [54].

Water systems in civilian neighborhoods around the country are similar. According to the Amarillo Globe-News, approximately 300 million gallons of potable water was wasted in 2013 due to routine maintenance in Texas 10 largest cities [10].

Water wasted due to decayed chloramine levels is unknown, but likely similar. Lack of optimization in water systems is the main cause of wasted water related to lifetime. Awareness of water shortages, installation of water conserving fixtures/appliances and an increase in stewardship over the past decade created an overall reduction ($\sim$ 13%) in per capita and overall potable water consumption [33]. Unfortunately, the reduction in consumption creates a new unintended consequence for the water system. Water systems are not optimized for the new reduced flow and further waste is created when excess treated water that reaches its disinfectant lifetime is potentially purged.

The energy consumed to treat, convey and store potable water is embedded in the water that is purged, creating more waste of a different form. According to the United States Environmental Protection Agency(EPA), 1,500 kWh of energy is typically consumed when providing one million gallons of potable water [35]. In the case of the aforementioned eight Net Zero installations, the 500 million gallons of water system losses account for approximately 750,000 kWh of wasted energy annually. If the study were expanded to all Army installations worldwide, the amount of wasted water, energy and capital would be substantial.

A typical, medium sized water system(a portion of the overall water system at Fort Carson, CO) will be studied in this dissertation. Because instrumental data are not readily available, it was necessary to use a case study method for this work. The author visited the system on Fort Carson, gathered data, and received valuable information regarding the dimensions and constraints of the various system components. Having this information helped ensure that the model developed in the following chapters was accurate. The water system studied here is also typical in that it has relatively little sensor technology or optimization and control implementation. Heuristically, the system operates in a manner that provides potable and safe water to the customers on Fort Carson. This work seeks to demonstrate the advantages of sensor implementation, optimization, and control of water resources on military bases.

1.2.1 Intelligent Water

Calls for technological innovation in the water industry have met with relatively minimal progress. Academic and government experts [7,29] have opined that to gain momentum towards improving our water systems, we must employ technologies much like the manufacturing industry. In contrast with the manufacturing industry, the water industry still relies largely on heuristic driven analysis and decision making that is both innacurate and labor-intensive. Ideally, the water industry, both civilian and military, would fully embrace large scale data acquisition, monitoring, and rigorous analysis. With large and various types of system data, models could be improved and controls could be implemented to provide efficiency that currently does not exist. Current efforts to employ 'intelligent water' systems is largely to improve monitoring of systems variables and conditions. Adding a control layer to these powerful data gathering and visualization tools will obviate the need for heuristics based control and allow for the implementation of system wide, integrated, automatic control to improve efficiency and lower cost. To avoid sub-optimal utilization of critical system data, analysis, and simulation, the integrated intelligent water and control framework must be integrated and transparent to all operators, enhanced by robust network infrastructure and data storage.

1.2.2 Chlorine Decay in Water Systems

Chlorines used to disinfect water to a potable condition are inherently unstable and undergo decay reactions once placed in the water system [61]. Once

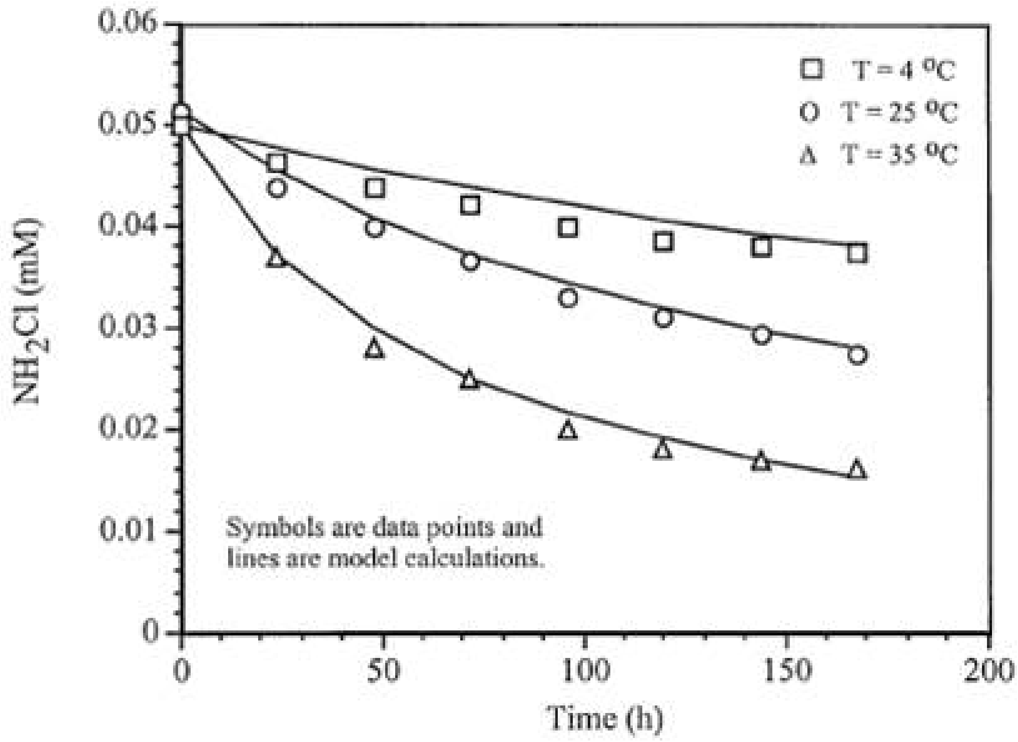

Figure 1.3: Chlorine decomposition in water as a function of time and temperature [61].

treated, water enters the system of interest and after sitting in pipes, pumps and tanks, eventually reaches the consumer. Local laws dictate the minimum safe chlorine concentration at the demand to ensure a safe supply of water (for this work, 0.2 mg/L). Ideally, all water that enters the system reaches a consumer before its chlorine concentration decreases below 0.2 mg/L. Water system operators are in a constant struggle to ensure that water reaches consumers prior its chlorine concentration decreasing below the minimum, often based solely on heuristics. Due to temperature effects, sporadic demand and system optimization, most systems experience times when they must flush the water system until chlorine concentration increases above 0.2 mg/L. Flushing, or essentially draining water onto the ground, is wasted water, energy and money.

1.2.3 Hierarchical Process Control

The hierarchical process control framework used in this work is shown in Figure 1.4 [50]. The hierarchical approach minimizes the complications associated with different time scales of phenomena in the system. The real time optimization (RTO) level ensures that all constraints are met while using day ahead electricity pricing and projected demand to schedule water pumping to maintain sufficient tank holdup. A secondary, yet important, effect of this layer is that it minimizes tank holdup from current known practice. The model predictive control (MPC) layer is the supervisory controller operating in the slow time scale, which uses the model and constraints to coordinate the control action of the feedback and feedforward loops in the regulatory control layer. The regulatory control layer consists of the feedback and feedforward control loops that stabilize the fast dynamics of the system and ensure their respective processes remain within limits while reacting to measured disturbances and set point changes from the MPC layer.

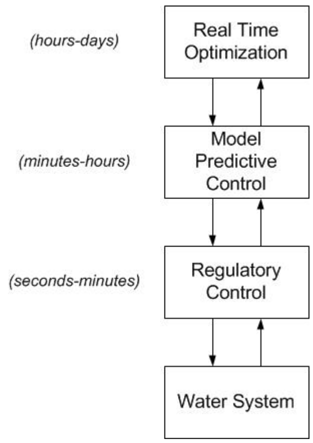

Figure 1.4: Hierarchy of process control in this work.(Seborg et al., 2011)

1.2.4 Optimization and Process Control Challenges

There are many challenges that have delayed the advancement of optimization and control of military systems. The challenge that has the most broad ranging effect is the lack of high fidelity, sensor acquired, system variable data. The vast majority of water consumption on military installations is not tracked [26]. Accurate and abundant data drives how demand is understood; when, where, and how water is used affects how it is managed. Military demand is different than their civilian counterparts. Often, individual buildings in close proximity or geographical areas have a variety of functions (maintenance, office space, living quarter, food service, etc.) [26]. Accurate data on all system variables is in short supply and if reversed, could significantly aid the improvement of system models. Other challenges include regional water stress and increasing water unit costs.

1.3 Literature Review

When considering the optimization and control of municipal water resources, the literature has two developed areas: optimization or minimization of water consumption and optimization and control of chlorine disinfectant. With respect to minimizing water consumption, a variety of techniques have been documented. Pinch analysis was used successfully in domestic water networks to avoid surplus treated water and avoid waste [24, 25]. Genetic algorithm techniques have also been employed to design water networks for efficiency, cost and resiliency [40, 58, 62]. A number of papers cover global optimization of water networks with a focus on cost and availability, particularly in chemical processes [8, 28].

Literature review details that are specific to each chapter only appear in those areas where applicable. Those areas are expanded where they are appropriate. To our knowledge, there is no evidence that the unique characteristics of military systems and their demand patterns have been accounted for by researchers. Further, optimization of systems to minimize flushing waste and tank holdup, whether civilian or military, has not been conducted in the literature. Therefore, these issues will be addressed specifically in this work.

1.4 Dissertation Outline

In this dissertation, the methodologies for optimization and control military water systems for reduced water and energy waste is discussed. Developing models and control structures that will replace current heuristic based approaches is explored. It is organized as follows:

Chapter 2 introduces an equation based water model and validates that model with data from the studied system at Fort Carson, CO. The relationship between residence time and chlorine degradation is explained. Discretization of partial differential equations describing water flow and chlorine concentration degradation are covered. Time step determination for the system of nonlinear partial differential equations is discussed. Unique characteristics of military water systems are discussed as well as current operating practices.

Chapter 3 describes a nonlinear optimization program that uses day ahead electricity pricing to schedule pumping. Constraints on system variables are implemented in a way that reduces tank holdup and lowers cost.

Chapter 4 builds on Chapters 2 and 3 to design and implement a nonlinear model predictive controller. The controller lowers cost, reduces waste, and maintains system variables within acceptable ranges under stress of large system disturbances.

Finally, Chapter 5 summarizes the scientific contributions made in this dissertation and provides a few recommendations for future research work.

While this work was intended to expand the knowledge base about water operations at military installations in the CONUS, clearly much remains to be done.

Given the importance and urgency of the topic, the author encourages future researchers to focus on ideas that will integrate large scale system data, optimization, control, and a robust digital infrastructure. The power of these tools together should have dramatic effects on water, energy, and capital savings.

Chapter 2

Water System Modeling

2.1 Introduction

Water systems around the country are unique in size, construction, demand patterns, operational strategies, and kinetics. Although the principles of water flow and chlorine concentration in the systems are universal, the accuracy of modeling water systems is often dependent upon site specific characteristics. There are approximately 155,000 public water systems in the United States and each of them would require special consideration to ensure accuracy [1]. Military water systems are similar to their civilian counterparts with respect to many characteristics, with some important differences that shape how systems are modeled [26]. Geographic proximity of different classes of water consumers, building utilization, constraints on operation strategies, and the potential for large unpredicted disturbances are all unique to military bases. Unfortunately, modeling of these systems to date has consisted of macro level water balances or micro level building modeling that does not contain influences from the greater system [26]. The work in this chapter seeks to establish an equation based distributed model that can be applied to future optimization and control efforts.

2.1.1 Literature Review

With respect to modeling water systems, the body of knowledge hinges upon one or two key papers [9, 46]. The most influential work in the field determined a discretization method called the Discrete Volume Element Method (DVEM), which treats each segment of discretized space as a completely mixed reactor [45,46]. Modeling improvements were later made on disinfectant by-products, chlorine degradation kinetics, and tank holdup behavior [47, 51, 60]. This work provided the basis for development of EPANET, a powerful modeling software package distributed free of charge by the United States Environmental Protection Agency. Comparisons of various lagrangian and eulerian methods of modeling water transport and chlorine degradation in water systems have been accomplished and the results are comparable when using the same methods [44].

The underlying principles for modeling water flow and chlorine degradation are well established in the literature. This work seeks to build on those advances and adapt them to the unique characteristics of military water systems, while validating with actual system data. Building a model subject to the unique demand patterns, constraints, and resiliency concerns of military water systems will aid in conducting follow on studies of system optimization and control.

2.2 Equation Oriented Water Distribution Network Model

2.2.1 Demand Data

The first step of this analysis is to construct a model of a representative system. Because this study refers specifically to the water systems on U.S. Army

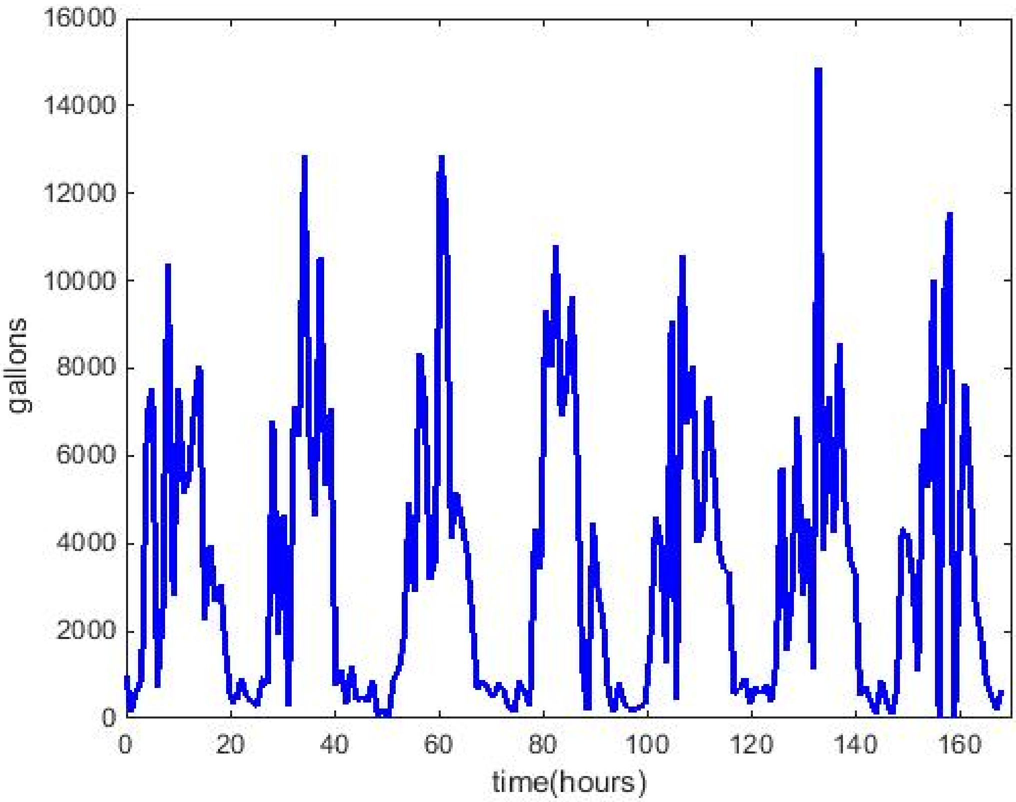

Figure 2.1: Water demand data used in this study, gathered over a 24 hour period from Pecan Street, Austin, Texas, scaled to a seven day period, and modified for a military/hybrid demand application. Source: Pecan Street Inc. Dataport 2016

installations, the model developed is specific to those systems with respect to demand patterns and constraints. As a part of this study, a case study was conducted on a portion of the water system at Fort Carson, Colorado (see Figure 2.3). Fort Carson is one of the Net Zero installations noted above, so the water use patterns are treated as similar to that in Figure 1.2.

Based on the average daily demand of water in the referenced system during

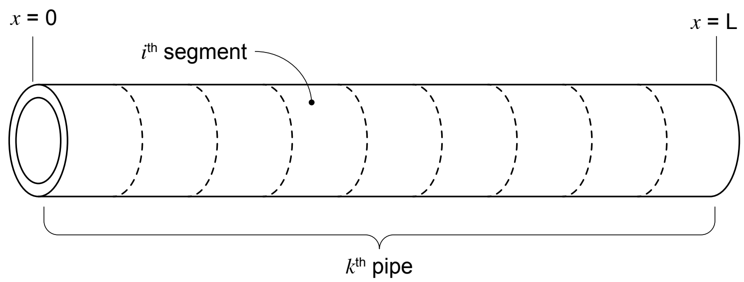

Figure 2.2: Graphic representation of each network pipe segment k with pipe segments, i.

summer months (approximated from actual system data), the total daily demand for this study was set at 82,000 gallons. Due to local law at the location of the system, this study used 0.2 mg/L as the minimum chlorine residual. Due to slightly varying local and state law across the United States, minimum chlorine residual is not constant geographically. All pipe lengths were scaled from maps of the system and actual pipe diameters were used.

Municipal water systems, to include military bases, typically do not meter, collect, and distribute high fidelity water usage data on a scale that is useful to researchers. This practical concern hinders efforts to fully investigate and improve water systems. As a reasonable substitute to model military water usage, a research data set gathered in Austin, TX was used in this study to build a representative water demand profile [18].

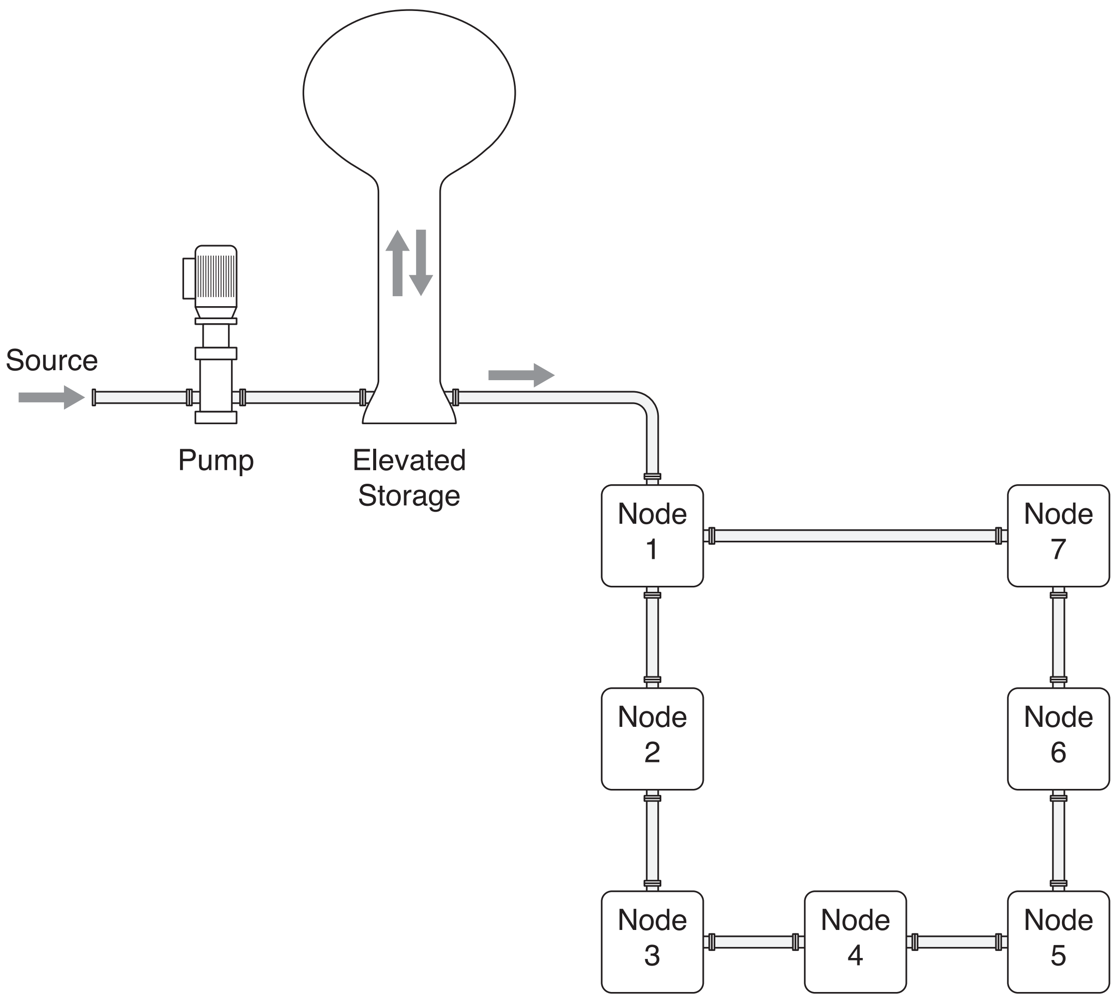

Figure 2.3: Diagram of the modeled system showing k pipes connected to all system components. Modeled system is a portion of the actual system at Fort Carson, CO. Each demand node represents a cluster of water consuming structures (houses, maintenance facilities, hospital) or activities.

Figure 2.1 depicts a modeled seven day pattern of water demand based on the Pecan Street data. A cluster of 697 days of residential water demand data from nine homes within the Pecan Street Project were scaled to create the demand curve representing approximately 82,000 gallons/day. The resulting water demand curve was then further scaled to shift the peaks of mostly morning/evening use to the hybrid demand pattern, showing peaks in the morning, afternoon, and evening. Military installations have demand patterns that differ from their civilian counterparts. They typically have residential and industrial areas in close proximity to one another while using the same water system. Therefore, the demand data depicts peaks in the morning, afternoon, and evening.

Using the aforementioned demand data, a discretized dynamic model of the system was constructed with respect to chlorine concentration, tank volume, reaction kinetics, bounds on relevant variables, and a linear cost objective function. Material balances were developed over all components within the system.

2.2.2 Mathematical Model

Let $c_{t,k,i}, t \in \{1, 2, \ldots, T\}, k \in \{1, 2, \ldots, K\}, i \in \{1, 2, \ldots, I\}$ represent the bulk flow chlorine concentration at time t in pipe k, pipe segment i. Let $q_{t,k}, t \in \{1, 2, \ldots, T\}, k \in \{1, 2, \ldots, K\}$ represent the volumetric flow rate at time t in pipe k. Let $v_t, t \in \{1, 2, \ldots, T\}$ represent the volume of water in the tank at time t. T is the number of hours in the model time horizon, K is the number of pipes, and I is the number of discretized axial volume elements in each pipe, k. N is the number of demand nodes in the network, where water is withdrawn for consumption (neighborhood, industrial/office building, etc.) Rossman et al. determined that there are two dominant mechanisms within the distribution pipe network that contribute to the first order kinetic nature of chlorine degradation. Chlorine residual degradation occurs in the bulk water and also, more aggressively, at the water/wall interface [46]. Using these assumptions, chlorine concentration in the pipe network is modeled as:

$$\frac{\partial c_{t,k,i}}{\partial t} = \frac{-q_{t,k}}{A_k}\frac{\partial c_{t,k,i}}{\partial x} - \theta c_{t,k,i} \tag{2.1}$$

where $c_{t,k,i}$ = chlorine concentration in the pipe bulk flow; $q_{t,k}$ = volumetric flow rate; A_k = cross sectional area of specific pipe, k. The term on the left side of Equation (2.1) represents the change in chlorine concentration in pipe segments throughout the water distribution network with respect to time. The first term on the right describes the change in concentration axially along length of each pipe segment, multiplied by the quotient of volumetric flow rate and cross sectional pipe area. It is this term that introduces nonlinear behavior to the model as the flow rate and concentration are changing simultaneously. The second term on the right describes the reaction kinetics multiplied by the chlorine concentration. $Theta$ represents the reaction kinetics of chlorine degradation as a function of time and temperature, outlined by Rossman et al [46].

$$\theta = k_b - \frac{k_w k_f}{r_h(k_w + k_f)} \tag{2.2}$$

where k_b = decay rate constant in the bulk; k_w = decay rate constant at the pipe wall; k_f = mass transfer coefficient; r_h =hydraulic radius of pipe. Chlorine concentration throughout the pipe network is modeled in a similar manner, only differing by the source concentration. For the purposes of (2.3) and (2.4) below, k' refers to pipes entering a demand node and k refers to pipes exiting a demand node. For each demand node, or junction in the network where water is consumed, a material balance exists in the form:

$$c_{t,k,i}\big|_{i=1} = \frac{\sum_{k'} q_{t,k'} c_{t,k',i}\big|_{i=10}}{\sum_{k} q_{t,k}} \tag{2.3}$$

For continuity across each demand node:

$$\sum_{k'} q_{t,k'} - \sum_{k} q_{t,k} - Q_n = 0 \tag{2.4}$$

where Q_n represents demand flow at each node, n. Because the ratio of volume to surface area in the storage tanks is much lower than that of the pipe network, it is assumed in this study that any reaction (degradation) of chlorine at the tank wall is negligible. It is also assumed that tanks are well mixed in this study. Therefore, to describe chlorine concentration in the tank as a function of time:

$$\frac{dc_t}{dt} = \frac{q_{t,k}}{v_t} c_{t,k,i=10} - \frac{q_{t,k}}{v_t} c_t - k_b c_t \tag{2.5}$$

where v_t is tank volume and c_t is the chlorine concentration in the tank. To represent the change in tank volume as a function of time, a simple mass balance is used, as follows:

$$\frac{dv_t}{dt} = q_{t,k}\big|_{in} - q_{t,k}\big|_{out} \tag{2.6}$$

where tank volume depends solely on in and out water flows and losses are negligible.

2.2.3 Discretization

Equations representing water flow and chlorine degradation in the pipe network (Equation (2.1)) were discretized in space using the method of lines [49]. After the method of lines was applied to the set of equations, they assumed the form:

$$\frac{\partial c_{t,k,i}}{\partial t} = \frac{-q_{t,k}}{A_k}\frac{c_{t,k,i} - c_{t,k,i-1}}{\triangle x} - \theta c_{t,k,i} \tag{2.7}$$

where $c_{t,k,i-1}$ is the chlorine concentration in the water when delivered from the source. This study uses a Gaussian distribution from 0.7-1.0 mg/L(mean 0.86 mg/L, standard deviation .082) to describe source chlorine concentration at each time t. This inlet concentration distribution is consistent with military water systems receiving water from outside sources; chlorination levels in the water as it arrives are not steady and have a distribution. The implicit Euler method was then used to discretize the set of equations in time.

$$c_{t,k,i} - c_{t-1,k,i} = [\frac{-q_{t,k}}{A_k}\frac{c_{t,k,i} - c_{t,k,i-1}}{\triangle x} - \theta c_{t,k,i}]\triangle t \tag{2.8}$$

Similarly, equations (2.5) and (2.6) were discretized in time.

$$c_t - c_{t-1} = [\frac{q_{t,k}}{v_t}c_{t,k,i} - \frac{q_{t,k}}{v_t}c_t - k_b c_t]\triangle t \tag{2.9}$$

$$v_t - v_{t-1} = [q_{t,k}|_{k=in} - q_{t,k}|_{k=out}]\triangle t \tag{2.10}$$

2.3 Simulation Results/Model Validation

Figure 2.3 depicts the model system with an intake, one pump, one storage tank (500,000 gallon capacity), and seven demand "nodes". Solving the model as a nonlinear set of equations with no constraints adequately simulates the current practice of civilian and military water systems across the nation. Tank holdup, or level of water, is maintained excessively high and well beyond the level of necessary emergency water supplies (75% of total tank capacity in this study). The unconstrained model operates similar to common industry practice, with two modes: *pumps on* and *pumps off*. Pumps are activated as needed and they remain on until the tank reaches the aforementioned excessively high water level, regardless of the time of day. (see Figure 2.4) Figure 2.4 depicts actual current operations on military bases that are similar to most, if not all, municipalities. After water is pumped into the tanks and the tank holdup reaches an upper constraint, the pump is turned off and the volume simply decreases over time as demand consumes the water. Figure 2.5 shows the results of modeling the unconstrained system, tank volume, pumping action, and associated demand patterns. The pumping pattern and duration in Figure 2.5, showing the modeled system, looks very similar to the same in Figure 2.4, which shows actual current pumping practices. The behavior of the model and the concentration of chlorine residual at the point of demand provide evidence that the model is reasonably accurate when compared to data gathered on site (Table 2.1). Further, concentration data in the model system differs negligibly between seasons. To validate the modeling approach, concentration data were gathered on Fort Carson, CO and compared to modeling results from this study.

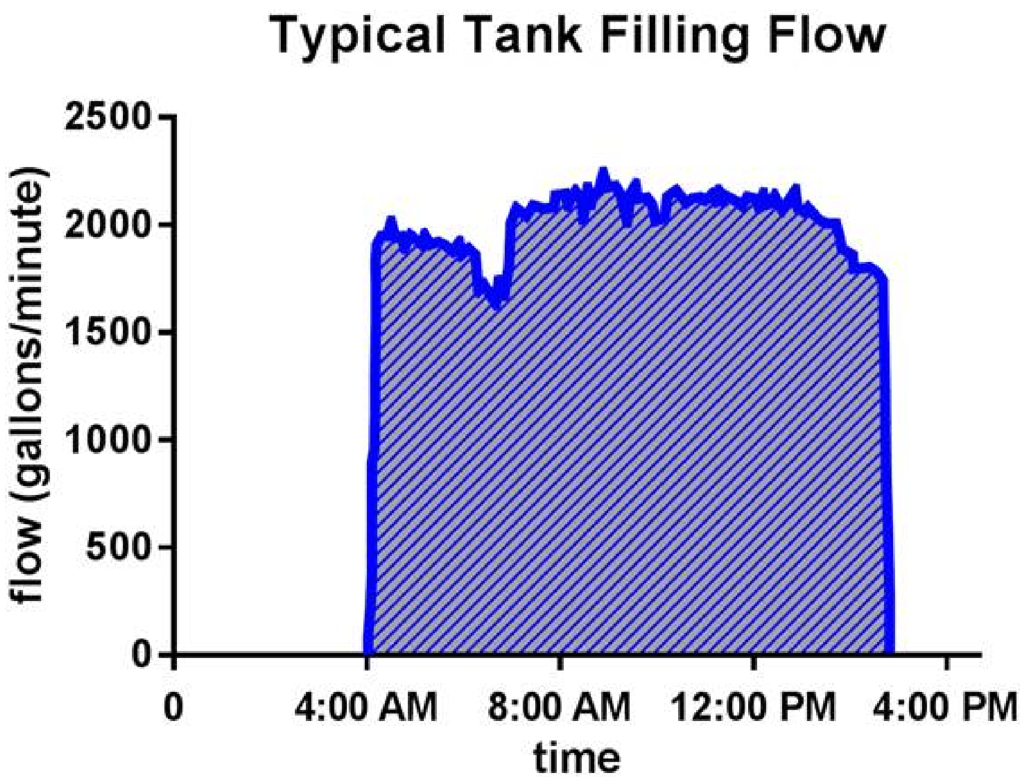

Figure 2.4: Current military base tank filling procedures are similar to most municipalities, filling as needed throughout the day and consuming excess energy (Plotted from actual metered data acquired on site)
.

Table 2.1 shows that the modeled chlorine concentration at node one is consistently between 0.4 and 0.5 mg/L while data taken from the actual system over a 48 hour period in February 2016 show the mean chlorine concentration to be 0.4 mg/L. In order to test the validity of the model based on a portion of the system at Fort Carson, Colorado, chlorine concentration data at node one and four and other installation locations was gathered manually using a Hach CN-66 total and

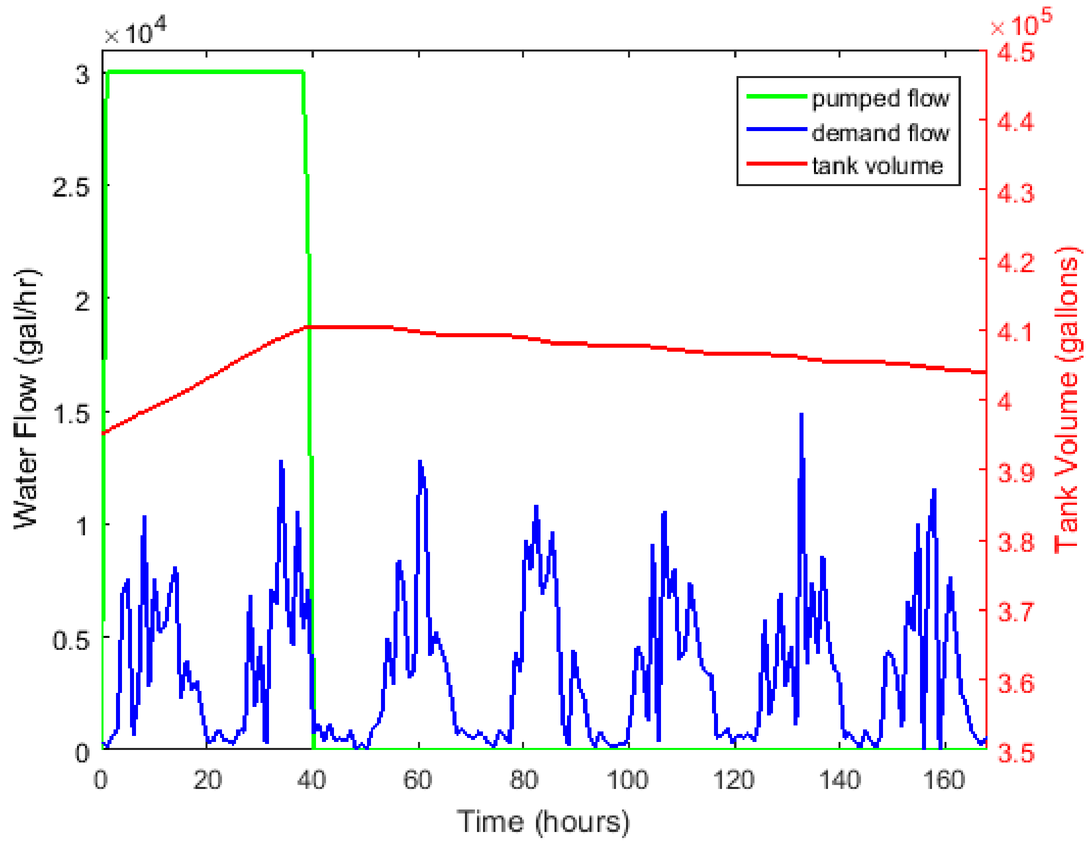

Figure 2.5: Model simulation of current operational methods showing demand, pumping flow, and tank volume over a seven day period. Traditional operations include over pumping the water on day one regardless of time of day, then letting demand reduce tank volume until the lower tank level constraint is reached.

free chlorine test kit. Like their civilian counterparts, military installations do not acquire and store high resolution water system data that can be used for modeling, optimization, and/or control. This study required on-site manual data gathering in order to gain any insight into system behavior. Through a network of contacts and the progressive attitudes of the team at Fort Carson, access was granted for this study. Close coordination with the Fort Carson Department of Public Works(DPW)

Time	Observed	Modeled
0800	0.51	.40
0900	0.55	.39
1000	0.51	.38
1100	0.50	.39
1200	0.52	.39
1300	0.50	.39
1400	0.48	.40
1500	0.50	.40
1600	0.52	.40

Table 2.1: Observed chlorine concentration (mg/L) obtained from manual samples at node one in the model system and corresponding modeled (unconstrained) values.

provided access to acquire measurements over the 48 hour sample period. Limited access on military installations for security reasons hinders the ability to gather large amounts of data. A security clearance and the appropriate permissions should ensure access to necessary areas, but the distance between sample areas of interest is vast and slows the data gathering process considerably. Figure 2.1 shows a portion of the acquired data for model validation. System pressure data was also gathered but not used in the study to date. Modeled concentration is highlighted and compared to observed system data to demonstrate the validity of the model. The slight disparity in values at every time observed is likely due to highly unpredictable source chlorine concentrations. Source chlorine values were observed to be between 0.7 and 1.0 mg/L but can vary greatly based on numerous factors that cannot be observed or controlled.

Sensor installation and soft sensor development would contribute greatly to water model accuracy. Currently, routine chlorine measurements to ensure compliance with local laws and regulations are taken manually. Further, their frequency is inconsistent, so there are ample opportunities for error. Inconsistent system parameter measurements leave operators with a knowledge gap that leads to inefficiency and the inability to rapidly and effectively react to emergencies and large disturbances. The desire to apply technology to water sensor employment and data acquisition have led to new buildings at Fort Carson, Colorado being built with these systems in place, but they are not connected to an interface and automatic data gathering is not taking place. Further, at least one chlorine injector is installed on Fort Carson but not connected to or controlled by a control framework outlined in this dissertation.

2.4 Time Step Determination

Time scales differ between the dynamics of a water system; water is consumed rather rapidly(hours), while chlorine within the water degrades at a much slower pace (days). For optimization of the NLP with these time scale variations, there exists a narrow band of time step values that will ensure numerical stability. Further complicating the computation is the constantly varying flow rate of water from the source on one end and at the demand on the other end. Courant et al. [16] described a condition for convergence of systems of nonlinear partial differential equations(PDE):

$$C = \frac{u \triangle t}{\triangle x} \leq C_{max} \tag{2.11}$$

where u = magnitude of the velocity, $\triangle t$ = time step within the system, and $\triangle x$ = the length interval. To efficiently determine a range of feasible time steps for models containing systems of nonlinear PDEs when volume elements and flow rates are involved, a condition similar to the Courant condition above is necessary. This study found that this condition will provide a reasonably accurate estimation for the necessary time step that will allow the system to converge. In the case of any system dealing with volumes in pipes, the condition is written as:

$$C = \frac{q\triangle t}{\triangle v} \leq C_{max} \tag{2.12}$$

where q = magnitude of the flow rate, $\triangle t$ = time step within the system, and $\triangle v$ = the volume interval.

$\triangle t$(minutes)	C_{max}	Time to Converge(% of most rapid)
1.17	.8	+4
1.32	.9	−
1.47	1	+11
2.22	1.6	+88

Table 2.2: Feasible time steps determined for this study and their corresponding C_{max} values in accordance with equation (2.12). Time to converge is shown as a percentage relative to the most efficient value, corresponding to a $\triangle t$ of 1.32.

Although the convergence conditions are similar in concept, the C_{max} for systems involving volumes in pipes for this system will not converge if greater than 1.6 or less than .8 when the system is solved using the implicit Euler method and the condition is applied in the area of most rapid flow (highest flow rate, shortest length of pipe). Table 2.2 shows that the range of values for the time step and C_{max} that ensure system convergence are relatively small. Further, time to solve increases as the time step deviates above or below the optimum value of 1.32 minutes. Because each system is different, percentages from the optimum convergence time are shown to give the reader an idea how solver performance may change as $\triangle t$ is adjusted. The difference in C_{max} exists because of the requirement to satisfy all equations, during all conditions of time, flow rate, chlorine decay, and pipe length/volume. These competing requirements ensure that the time step is limited to a very narrow range less than 2.22 minutes and greater than 1.17 minutes that will vary slightly as network sizes and conditions vary. Future work related to water systems can consider time steps in this range as an excellent starting point for analysis.

2.5 Conclusion

In conclusion, the multivariable model in this work accurately describes water flow, consumption, and chlorine degradation in a military water system. The model, describing water flow through the pipe network and chlorine concentration degradation, provides a framework for further analysis. This work builds on the work of Rossman et al. by accounting for the challenges, demand patterns, and safety and resiliency constraints of military installations. The model developed, and validated with data from Fort Carson, CO, is accurate and provides insight into how water is distributed in the model system. This work can be adapted to other military water systems to assist in analysis.

Chapter 3

Optimization of Water System Operation

3.1 Introduction

The United States Environmental Protection Agency (EPA) predicts that due to population growth the water related energy demand will rise as much as 25% prior to 2023 [2]. Widespread drought throughout the United States over the past few years has focused attention on conserving water resources. Currently, many water systems, including the one referenced in this study, do not optimize operations with respect to tank holdup or pump scheduling (Please see Figure 2.4). Instead, operations observed by the author are conducted based on heuristics passed on among colleagues and monitored using a limited amount of data. Optimizing pump scheduling to reduce overall capital expenditures should minimize costs as pumps are activated only when electricity pricing is low. Minimizing tank holdup will save both capital and water because less water pumped and treated leads to less cost overall. Tank levels in water systems across the military's inventory of water systems are also managed on an heuristic basis. The approach generates excessive water volume in the system, which can lead to waste if residence time is extensive.

This chapter describes a model that seeks to minimize multiple critical components simultaneously: cost, tank water holdup, water consumption, and electricity consumption. Indirectly, the work will minimize carbon emissions, degradation by-products, and chlorine consumption.

3.1.1 Literature Review

Various methods have been used effectively to optimize domestic water systems for minimal pumping cost and optimal water quality [15, 22, 37, 38, 59, 63, 64]. Previous focus was correctly placed on lowering pumping cost and energy demand as the cost of conveyance within a system continues to be the highest operating expenditure for municipal systems [23]. Although the aforementioned work is extensive, this chapter seeks to fill the knowledge gap that exists with respect to military requirements and their unique constraints.

3.2 Optimization

This work uses nonlinear programming (NLP) and seasonal and geographic specific demand data to optimize the equation-based model system to reduce excess volume in the system, while minimizing pumping cost and maintaining quality. The author seeks to provide the military with a operationally based solution that will carry minimum cost, as opposed to a capital intensive proposed solution that is much more challenging to implement.

A contributing factor to excess volume in water systems is storage tanks and reservoirs that are either oversized or operated inefficiently. They are often operated using heuristic knowledge alone, leading to inefficiencies and excessive cost. Many were installed prior to a decline in overall demand over the past few decades spurred by drought, conservation and awareness [33]. Heuristic volume constraints that were either implemented based on different demand or poor assumptions ensures excess volume that must be conveyed at a cost.

The NLP developed below, along with the model outlined in Chapter 2 and the specific demand pattern, accounts for the unique characteristics and constraints of military installations.

$$
\begin{aligned}
\min_{q_t} \quad & \sum_{t=1}^{T} E_t \\
\text{s.t.} \quad & E_t = \frac{0.746 * q_t * h * r(t)}{3960 * \mu_p * \mu_m}, \quad \forall t \in \{1, 2, \ldots, 168\} \\
& q_{t,k,x} \geq 0, \\
& \qquad \forall t \in \{1, 2, \ldots, 168\}, \forall k \in \{1, 2, \ldots, 9\}, \forall i \in \{1, 2, \ldots, 10\} \\
& \left.\begin{array}{l} Q_{t,n} \geq 0 \\ c_{t,n} \geq c_{min} \end{array}\right\} \quad \forall t \in \{1, 2, \ldots, 168\}, \forall n \in \{1, 2, \ldots, 7\} \\
& \left.\begin{array}{l} v_t \geq v_{lower} \\ v_t \leq v_{upper} \\ q_t \leq q_{max} \end{array}\right\} \quad \forall t \in \{1, 2, \ldots, 168\}
\end{aligned}
\tag{3.1}
$$

where $r(t)$ = sample hourly electricity rate which, for this study, ranges from \$0.02 – \$0.18 and follows well known pricing patterns (highest in the afternoon, lowest at night). h = pump head, or tank feed height above the ground (assume constant). Pump efficiency, μ_p and motor efficiency, μ_m are both set at 0.9 for this study. The symbol q_{max} represents the maximum flow rate allowed into the tank determined by pump capacity. The objective function above neglects to account for the purchase cost of water from the source because it is relatively constant and insignificant compared to the cost of electricity. The model also assumes a fixed fluid inlet to the water tank at 120 feet (based on actual tank drawings).

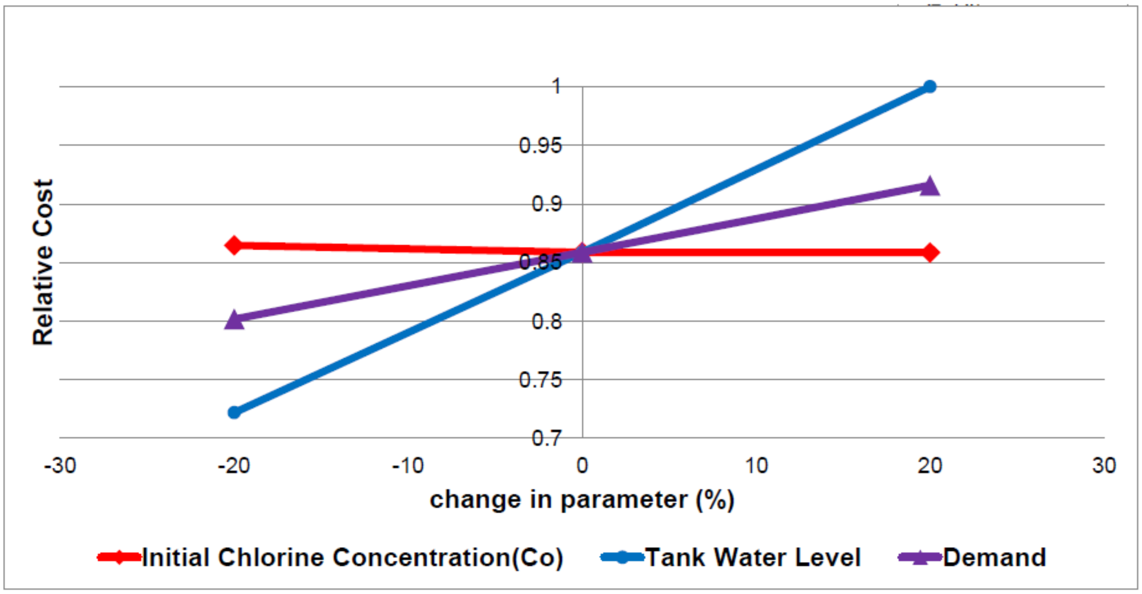

Figure 3.1: Sensitivity analysis conducted to determine system parameter influence on the objective function in (3.1). The objective function was measured as each parameter was adjusted +/-20% and shows that reduction in tank water level will have the greatest impact on cost and energy savings.

3.2.1 Sensitivity Analysis

Sensitivity analysis in Figure 3.1 demonstrates the sensitivity of the objective function to 20% changes in system parameters. Initial concentration has little to no effect on cost and customer demand predictably has some effect on cost. The cost of providing water to a distribution system is most sensitive to the level at which the water is stored in the tank(s). This cost is driven by the embedded pumping and conveyance cost for each gallon stored above what is absolutely required. Because this parameter will have the greatest effect on overall cost and therefore excess water consumption, this study focuses on systematically reducing the water level while maintaining service and satisfying all constraints.

The nonlinear optimization program was solved using CONOPT [21] in the General Algebraic Modeling System (GAMS) [43] environment(see Appendix). Upper and lower bounds were imposed on the decision variables that were reasonable or met specific system criteria. For instance, the lower bound on $c_{t,k,i}$ is dictated by local and state laws while the upper bound on $q_{t,k}|k = 1$, the flow generated by pumping prior to the tank(q_{max}, above), is set in accordance with actual pump limitations in the model system. The solution time was 11 minutes on a Windows PC with a 2.1 GHz, Intel Core i7 Processor and 8 GB RAM. The converged nonlinear program consisted of 17,047 equations and 17,305 variables.

3.3 Results and Discussion

The objective function in the NLP actually serves two purposes: it directly reduces the cost of pumping water and minimizes the volume of water pumped, which saves money, energy, and emissions. In addition to upper and lower constraints on tank holdup, the objective function limits the treated water that is introduced into the system. Once optimized, the program ensures that, in accordance with the constraints above, pumping is avoided when rates are higher. The results are evident in Figure 3.3 where pumping occurs during the hours of darkness and demand continues as needed. Pumping periods are variable as the NLP adjusts for the varying

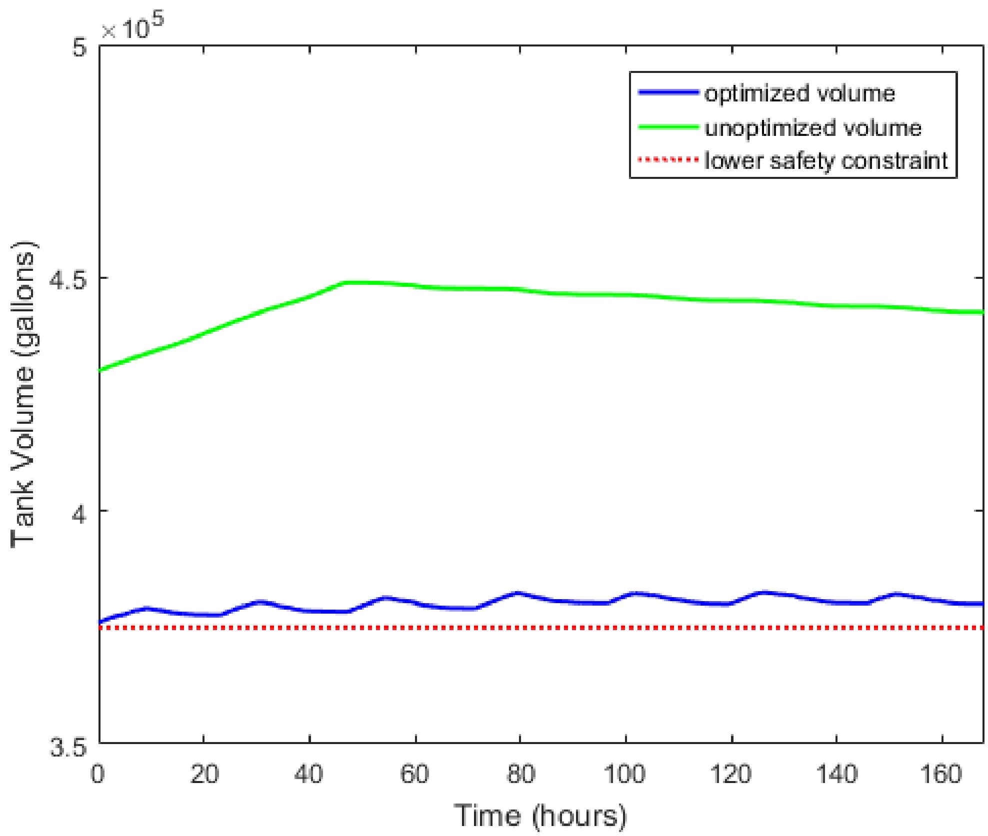

Figure 3.2: Comparison of tank volumes optimized under varying constraints after applying the optimization program. The minimum safe volume is a safety factor in case of an emergency, terrorism, or natural disaster.

demand prediction. The efficiency of the program and relatively brief solving time allows for easier implementation of operational changes.

When comparing the operational strategies in Figures 2.5 and 3.3, there is one result that is not obvious. Because the objective function in equation 3.1 seeks to minimize pumping cost, it is possible under isolated circumstances that the optimized strategy identified in Figure 3.3 would actually pump more water in an effort to keep costs down. A situation when prices are low and demand is high could create this scenario. A future addition to the NLP outlined above may include an additional objective function that minimizes pumping, but constraints in the current NLP that seek to limit tank volume were sufficient to meet the objectives of this study.

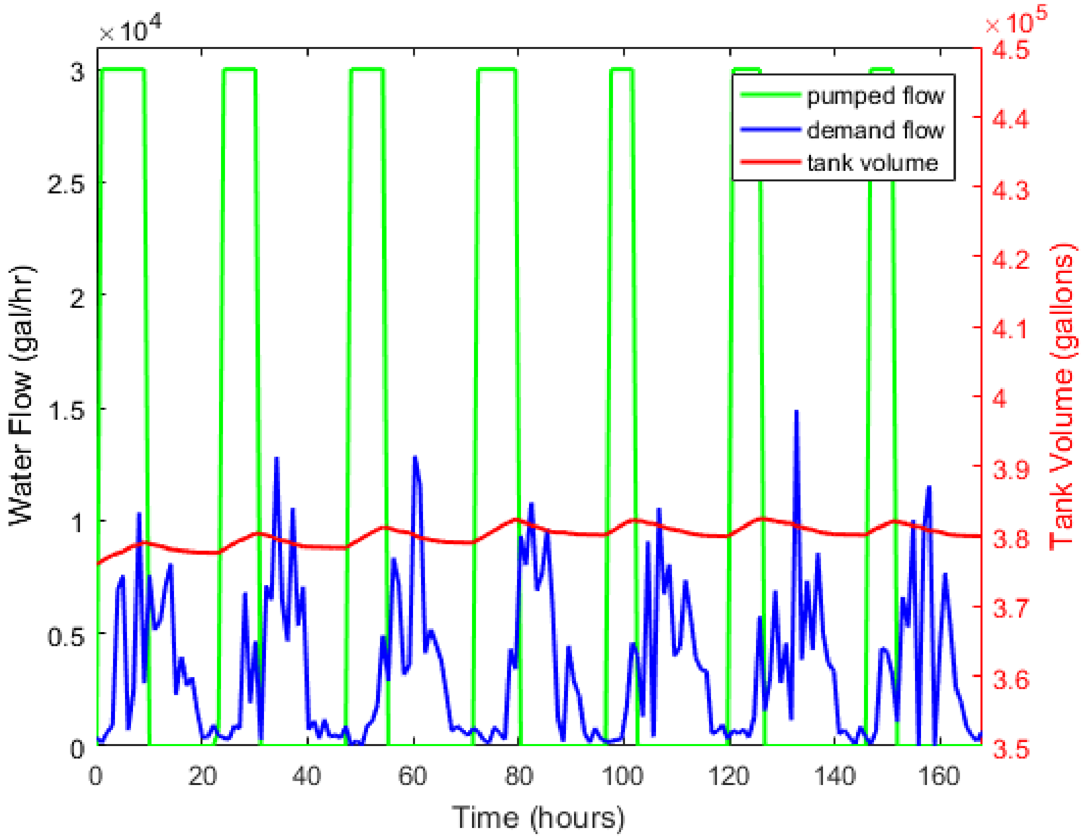

Figure 3.3: By contrast with the conventional approach, which pumps water regardless of time of day, this approach spreads the pumping out over multiple days during off peak hours, reducing cost and keeping tank volume near the lower constraint.

Further money and energy savings can be realized when optimizing the holdup of tanks in the system. Using predicted demand patterns, the NLP computes ade-

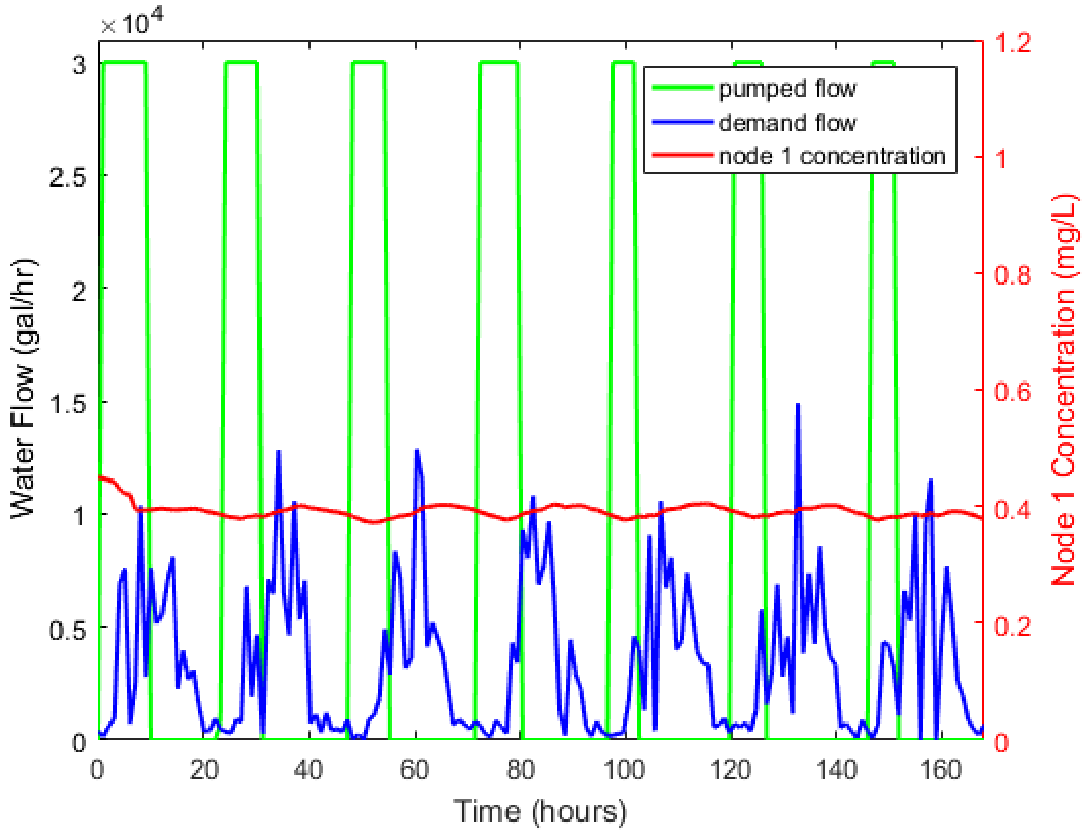

Figure 3.4: Optimized chlorine concentration at node one over a seven day period.

quate holdup to meet that demand while ensuring that the overall tank holdup is minimized. Due to decades of operating without rigorous optimization of operational practices, typical tanks are operated in a level range that is above the minimum safe volume but because rigorous optimization has not been applied, this operating zone within the tank is not at the optimum level. The tanks are typically operated at an artificially high, heuristically determined, level. The tank(s) must be operated in a zone, or range, instead of a tightly controlled level due to unpredictable demand and the need to pump in off-peak hours. Operating in a band of volume gives the NLP a type of flexibility to meet all of the constraints. To minimize water usage and energy consumption, an optimized system would need to operate in a zone just above the safety threshold (75% of total volume in this study), consisting of a fraction of the total tank volume, allowing for flexible response to demand and pumping flows. If the optimal zone is allowed to increase over time and if not quantifiably determined, excess volume will exist in the system and will likely not be consumed before its chlorine concentration degrades below the legal limit. This holdup creep, or artificial expansion of volume based on heuristic analysis, is a large source of waste due to excessive holdup. Once excess volume is allowed to accumulate in the system that exceeds demand, the excess volume must be wasted in the form of flushing water from the pipe network.

For instance, Figure 3.2 depicts two sets of constraints on tank level implemented and used to optimize the model. The red dotted line depicts the typical safety/emergency holdup that serves to protect the community during unforeseen circumstances (pipe malfunction, terrorist activity, large fire, excess demand based on operational need). To reduce water and energy consumption while still maintaining the required safety/emergency volume, the lower constraint should be implemented. The upper constraint represents current operating strategies depicted in Figure 2.5, is feasible, satisfies the safety constraint, and is common practice in water systems, but maintains a wasteful amount of excess water on hand. In times of low demand this excess water will potentially be wasted at least in part, as well as the energy consumed to treat and convey. Implementing a lower constraint volume is difficult without a rigorous optimization method to ensure continued reliability. This work provides the modeling and optimization framework to safely implement this type of control.

Providing safe drinking water to customers over extensive geographical areas is, after all, the main objective of water systems. Figure 3.4 is evidence that despite the competing requirements of constraints, demand, and system parameters, the optimization scheme ensures that demand chlorine concentration is maintained well with constraints and follows closely with validation data obtained in Table 2.1. The result reinforces the model's accuracy. Figure 3.4 shows that demand chlorine concentration will decrease when demand is low during the night and increase when chlorine enriched water is introduced to the demand side when demand increases. Demand chlorine concentration will decrease when tanks are filling and demand is low as that inventory is simply remaining in the tank until demand requires it to enter the demand side.

The difference in water and energy consumption by simply implementing one constraint over the other for this model is striking. By choosing to implement the lower volume constraint under the optimal pumping scheme outlined above, a volume savings of over 130,000 gallons is realized in the seven day modeling period. This water volume savings equates to $95 in savings during that same time period. For the sake of this example, assume that every Army installation in the continental United States, of which there are 100, has three of these systems (source, tank, pump, demand nodes). The case outlined above represents an 11% decrease in water pumping, storage, treatment, and conveyance, while meeting all constraints, demand,

and reducing waste. If optimization was implemented Army wide using the above model as a guide and if the impacts were similar, the Army would save over \$28,000 in a week or \$1,500,000 annually. The rigorous application of optimization in this case saves money that can be used to improve other areas of an already constrained military budget.

3.4 Conclusion

Optimization of the nonlinear model shows extensive improvement with respect to reducing water use and the cost of providing water. The model is efficient and robust, allowing its application to subsystems of any network. This work specifically targets excessively conservative operational practices exercised in most water systems that ensure clean water but are costly and potentially waste water. Improvements using this scheme are low or no cost and simply require changes in operational practices. Current oversized tanks and pipes may remain in place. Past practices, because of the low cost and abundance of water, have been acceptable but a new paradigm of water shortages will drive up costs and the need to reduce waste will be economically driven. Previous work focused on controlling chlorine and optimizing networks, but did not adequately focus on reducing waste because the incentive did not exist. This work is also unique because of the nature of military demand and constraints. As mentioned, military bases have a mixture of industrial and residential demand patterns, further complicating the model. Constraints on the system with respect to security, resilience and force protection are unique as well.

Chapter 4

Model Predictive Control for Disturbance Minimization

4.1 Introduction

This chapter proposes a model predictive control (MPC) supervisory layer, depicted in Figure 1.4, to minimize large, unpredicted disturbances while maintaining the strict constraints of military water systems. MPC is a tool used effectively in various process applications throughout industry [41]. If a reasonably accurate model is available, MPC is a suitable choice to provide supervisory control over processes like water networks where multiple inputs and outputs exist and strict inequality constraints must be met. Chapter 2 demonstrates the accuracy of the model applied in this dissertation, based on the work of Rossman, et al. [46]. MPC implemented in this work will solve an optimal control problem under constraints with a specified prediction and control horizon. The controller will calculate control moves over the entire control horizon, but only implement the first move before repeating at the next time interval. At each time interval after implementing the first control move, the controller is providing inputs to change the trajectory of the controlled variables to their desired set points [50]. This chapter's goal is to demonstrate the effective use of MPC on a military water system to reduce cost, water use, and ensure sufficient water inventory is maintained to establish resiliency in the system during times of stress on the system (large, unpredicted disturbances).

4.1.1 Literature Review of MPC for Water Networks

Led mainly by Mietek Brdys over the past two decades, a relatively small number of researchers have attempted to model and implement model predictive control (MPC) on municipal water systems. MPC was successfully applied originally to minimize the cost of pumping [37,38,59,64]. Others took a more general approach using MPC, gaining good optimization and control of water quality and quantity in municipal systems as a whole [11, 12, 15, 20, 22, 63]. An excellent feature article was published in 2002 providing an overview of feedback control as it applies to water quality [39]. A couple of key papers expand on the application of MPC to water systems by making improvements to the controllers or reducing uncertainty in the algorithms [14, 57].

Even fewer researchers have used feedforward compensation in efforts to control water networks. The literature shows that the only mention of feedforward control action implemented with model predictive control in water networks is by Sandison [48]. Sandison implemented feedforward compensation on single loop systems with good results, but it is unclear how well the framework would perform under the stress of large inlet disturbances.

A knowledge gap exists in the literature in three areas that will be addressed here: (1)NMPC for the reduction of system volume and storage holdup, (2)feedforward integration to minimize disturbances, and (3)applying NMPC to reduce cost, electricity consumption and increase system resiliency under the unique constraints of military water systems.

4.1.2 Motivation and Scope

Figure 3.1 shows that the cost of providing potable water is mostly sensitive to tank water level. Tank water level does drive cost in most, if not all, water systems because pumping water into the system is the only MV available. When chlorine concentration descends below the minimum level because of residence time or a disturbance on inlet concentration, the only MV to manipulate in water systems to change the controlled variable(CV), $c_{t,k,i}$, is pumping flow, $q_{t,k}$. Especially when disturbances are excessive, a possibility on military bases, manipulating $q_{t,k}$ as the only MV to change $c_{t,k,i}$ will inevitably lead to excess water introduced into the system. The implication of introducing water in excess of demand is that it will most likely be wasted, or purged, after the chlorine concentration descends below the minimum. An alternate framework that will specifically target the prospect of disturbances on inlet concentration and demand while meeting the goals of the optimization layer introduced in Chapter 3 is introduced here. The objectives of this chapter are to: (1)implement local regulatory control loops for tank water level (feedback) and inlet concentration (feedforward), (2)develop a nonlinear multi-input multi-output (MIMO) NMPC controller to regulate the CVs with adequate MVs, (3)compare the performance of the MIMO MPC controller to regulatory control alone, (4)integrate chlorine injection as a manipulated variable, and (5)demonstrate the effectiveness of feedforward control on large scale disturbance rejection while minimizing cost and tank water level.

4.2 Perturbations on Water Networks

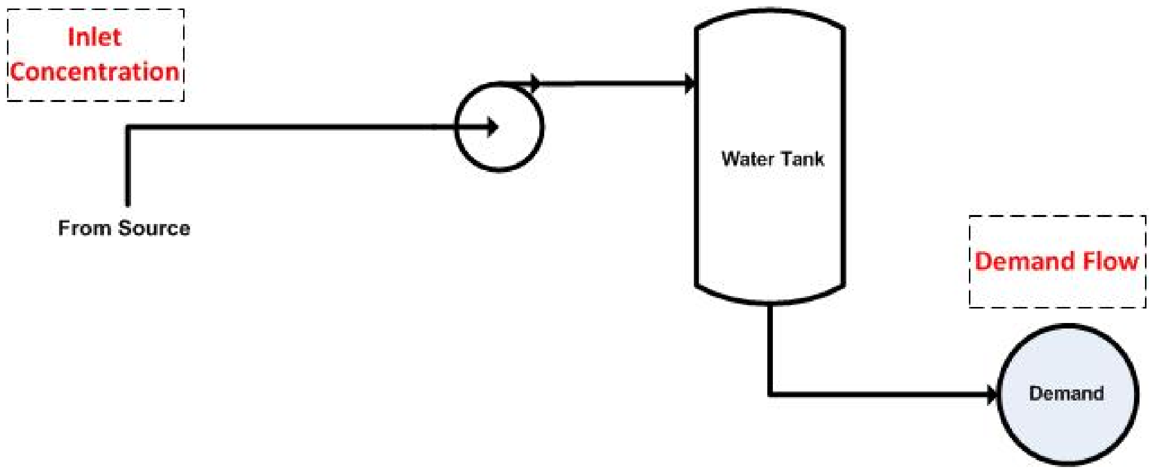

Figure 4.1: Locations of perturbations used in this study for demand and inlet concentration to demonstrate the effectiveness of MPC.

Large perturbations in municipal water systems are not unique to military bases, but the need to rapidly and accurately correct for disturbances is critical to base resiliency and safety. Resiliency on military bases is vulnerable to deficiencies in water systems created from a variety of disturbances: fires, terrorist activity, large leaks, or loss of chlorination at the inlet. Fires or large breaks in water lines caused by terrorist activity or other natural disasters, create an immediate and unpredicted demand that, without compensation, will quickly deplete water inventory. A large mechanized unit returning from training that requires large-scale cleaning and maintenance could also put a similar stress on the water system. Figure 4.1 shows the physical location of perturbations used in this study, while Figure 4.2 shows plots of the relative disturbances. This study simulates a disturbance on demand, similar to the ones mentioned above, in the middle of the day when demand is already high.

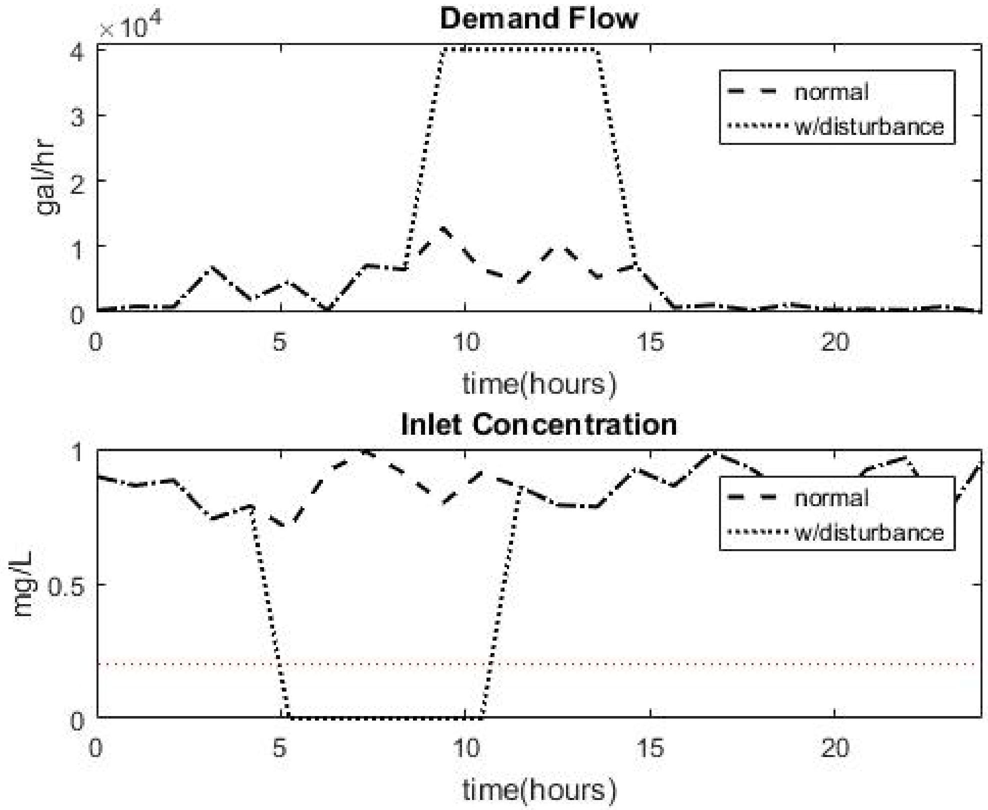

Figure 4.2: Simulated disturbances used in this study for demand and inlet concentration.

Further, Figure 4.2 shows a substantial disturbance on inlet concentration that, if not compensated for, would degrade water quality throughout the system and require extensive flushing that creates wasted water and energy. Although these perturbations are only a fraction of the possibilities, they were chosen for this study to show the rigor of the MPC framework because they are large and occur when the system is under the most stress.

4.3 System Identification

	Tank Holdup, CV	Demand Chlorine Concentration, CV
Pump, MV	$G_{11} = \frac{0.5067}{s+.00022}$	$G_{21} = \frac{4.4\times10^{-7}s+2.7\times10^{-7}}{s^2+.61s+.003}$
Chlorine Injection, MV		$G_{22} = \frac{-.1568s+.31}{s^2+.12s+6.6\times10^{-10}}e^{-4s}$
Demand, DV	$G_{13} = \frac{-.5341s+.0005}{s^2+.0009s+4.3\times10^{-9}}$	$G_{23} = \frac{-1.0\times10^{-5}s^2-1.4\times10^{-6}s+4.3\times10^{-6}}{s^3+15.5s^2+10.66s+.01}$
Initial Concentration, DV		$G_{24} = \frac{-.07s+.51}{s^2+4.4s+.96}$

Table 4.1: Individual step-response models for the identified water system in Figure 4.4 with four inputs and two outputs. The two blank plots represent no influence from inputs on CVs.

A multi-input, multi-output (MIMO) transfer function model was identified to accurately predict tank water volume, v_t, and chlorine concentration at demand, $c_{t,n}|n = 1$ as a function of four inputs: (1)pumping action, (2)chlorine injection, (3)demand flow, and (4)inlet concentration. Step changes were made in each input in the distributed model outlined in Chapter 2 and the results of the system identification is depicted in Figure 4.1.

The System Identification Toolbox™ in the MATLAB® software package was used to identify transfer function models for each input/output combination. The relationship between each input and output was captured with at least a 74% fit, so the transfer function models were used in the development of a model predictive controller. The positive result of system identification is evident in Figure 4.3 where the distributed model and transfer function model describing tank level are very

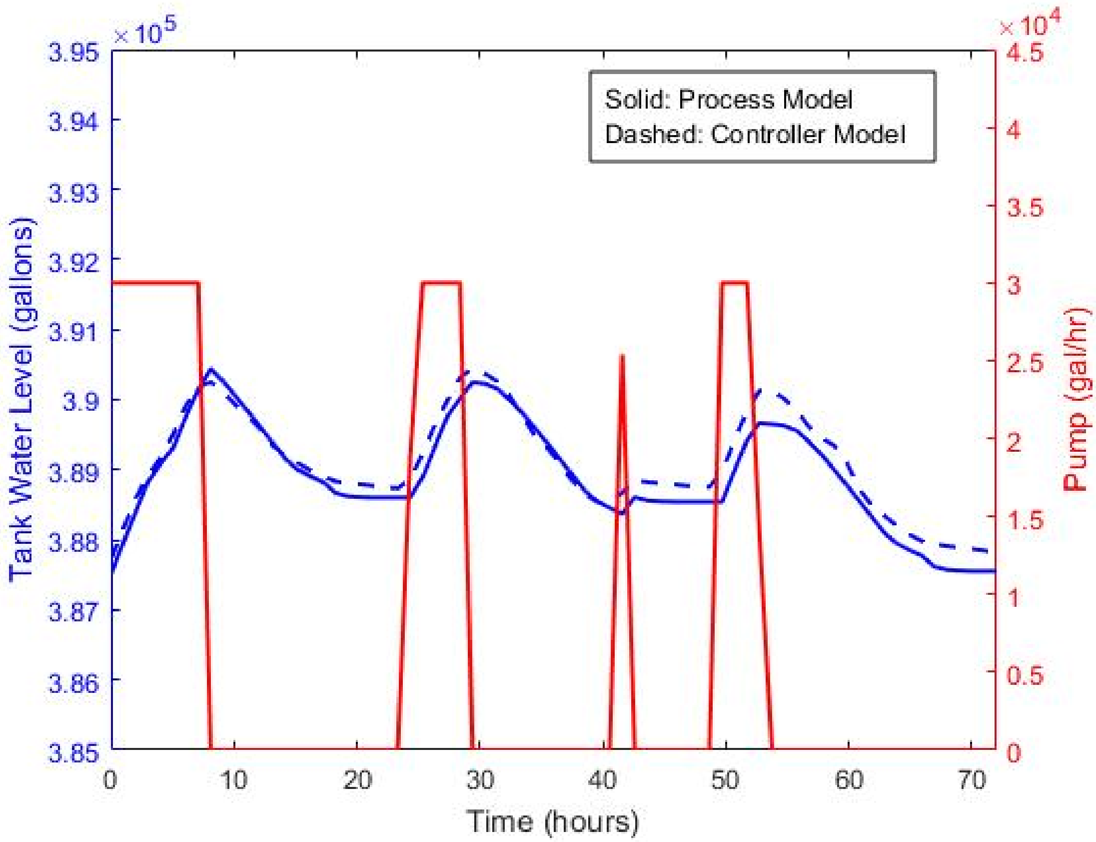

Figure 4.3: Comparison of tank water volume predicted by distributed modeling outlined in Chapter 2(solid) and the transfer function models shown in Figure 4.1(dashed).

similar. A common practice in MPC development is to use step-response models instead of transfer functions, particularly in highly nonlinear cases [50]. This work did not yet explore the use of step-response modeling to describe the water system and to the author's knowledge, this technique has not been used in water system modeling.

4.4 Nonlinear Disturbance Controller Development

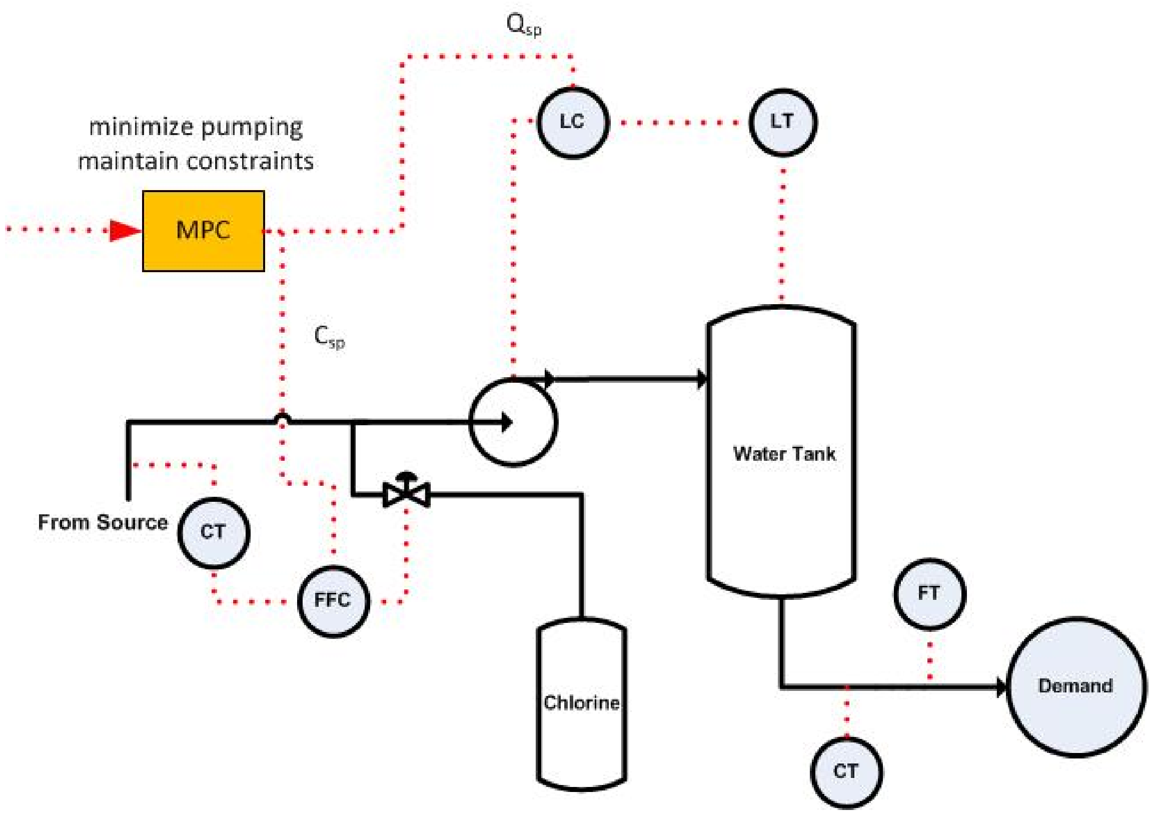

Figure 4.4: MPC framework with feedforward and feedback structure for disturbance compensation.

If a disturbance can be detected before it enters the process and the process model is sufficiently accurate, feedforward MPC can often provide better disturbance rejection than feedback MPC alone [13]. Most feedforward systems use feedback trim as a means to compensate for errors in modeling and feedforward control discrepancies. However, self-regulating systems that do not require set point tracking, like chlorine concentration in water systems in the presence of large disturbances, can be controlled adequately with feedforward control alone [52].

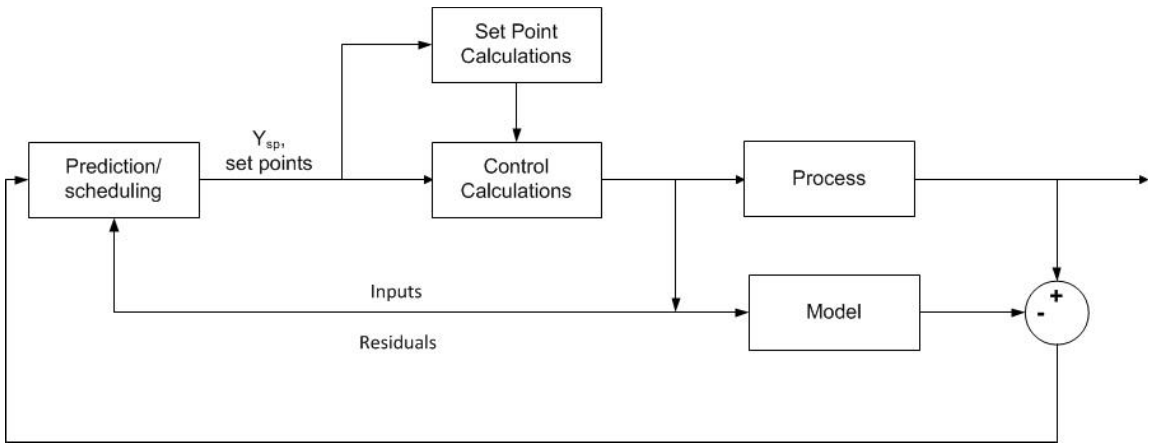

Figure 4.5: Block diagram for model predictive control with feedforward disturbance compensation. Modified from Seborg, et al. [50].

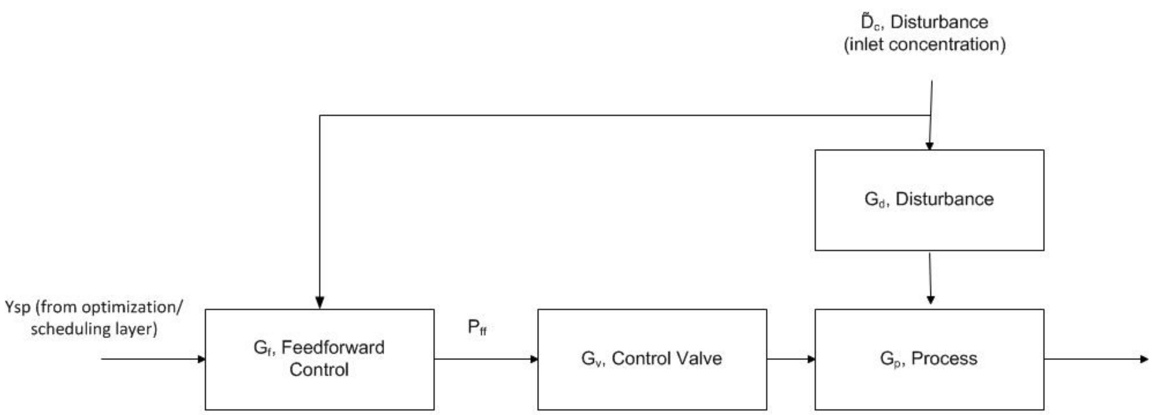

Figure 4.6: Block diagram for feedforward control. The control action is a portion of the "control calculations" block in Figure 4.5. Modified from Seborg, et al. [50].

This chapter outlines a nonlinear model predictive controller (NMPC) utilizing a dynamic system model, illustrated by the process flowsheet in Figure 4.4 and the block diagrams in Figures 4.5, 4.6, and 4.7 that utilizes two control loops to reject large process disturbances: (1)a feedback loop that rejects large disturbances

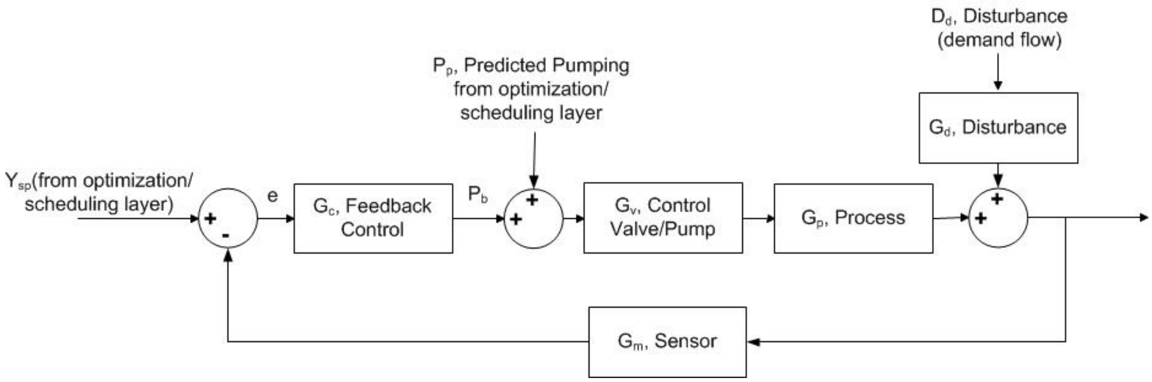

Figure 4.7: Block diagram for feedback control with included planned pumping from the optimization/scheduling layer. The control action is a portion of the "control calculations" block in Figure 4.5. Modified from Seborg, et al. [50].

on demand, maintains tank holdup above the minimum resiliency constraint, and minimizes the amount of water inventory on hand and (2)a feedforward loop that rejects large disturbances on inlet concentration to ensure that downstream chlorine concentration remains at acceptable levels.

The "control calcuations" block in Figure 4.5 is made up of the feedforward and feedback loops in Figures 4.6 and 4.7. The optimization/scheduling layer provides set points to the control loops based on the models prediction and inputs on the system such as electricity prices, predicted demand, and inlet concentration. Further, the optimization/scheduling layer provides predictive pump scheduling for the system, which is shown as an input to the feedback control loop in Figure 4.7.

The nonlinear nature of the model, outlined in Chapter 2, requires that the NMPC problem be formulated using a two phase approach: estimation phase and control move calculation phase [13]. The estimation phase is stated here as a nonlinear sub-problem:

$$\min_{\boldsymbol{x}_0,\boldsymbol{p}_e,\boldsymbol{d}_e} \sum_{l=0}^{p} \hat{\boldsymbol{E}}^T(k+1)\boldsymbol{Q}\hat{\boldsymbol{E}}(k+1) \tag{4.1}$$

subject to:

$$\begin{aligned}
\boldsymbol{x}(t-P) &= \boldsymbol{x_0} \\
\frac{d\boldsymbol{x}}{dt} &= f(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{p}_e, \boldsymbol{d}_e, t) \\
\boldsymbol{y} &= g(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{p}_e, \boldsymbol{d}_e, t) \qquad (4.2) \\
\boldsymbol{y}^m_{k-P+l} &= \text{measured value of } \boldsymbol{y} \text{ when } t = t_{k-P+l} \\
\hat{\boldsymbol{E}} &= \boldsymbol{y}(t_{k-P+l}) - \boldsymbol{y}^m_{k-P+l}
\end{aligned}$$

where $\boldsymbol{x}$ represents the controlled states, tank water level and chlorine concentration at demand, $\boldsymbol{p}_e$ and $\boldsymbol{d}_e$ represent estimated system parameters and disturbances, respectively and $\boldsymbol{y}(t_{k-P+l})$ and $\boldsymbol{y}^m_{k-P+l}$ represent predicted and measured output, respectively. The prediction horizon, P, is 24 hours in this study due to the accessibility of day ahead electricity pricing.

Similar to a linear case, the control move calculation phase is used to calculate the current control action, $\boldsymbol{u}_k$, plus additional control action and minimize the calculations over the control horizon, M. This work uses two control loops to calculate control moves: a feedback loop to control tank water holdup and a feedforward loop to control chlorine injection in an effort to minimize the effects of large disturbances on inlet chlorine concentration. The feedback loop utilizes a simple proportional control method to allow for averaging level control. Proportional control is also adequate in this case because offset is not a consideration.

$$P_b = \bar{p} + P_p + K_b e \tag{4.3}$$

In equation (4.3), $\bar{p}$ represents the steady state value, P_p is the scheduled pumping action passed from the optimization/scheduling layer, and K_b is the proportional gain for the feedback loop [50]. The error, e is defined as:

$$e = Y_{sp} - Y_m \tag{4.4}$$

where Y_m is the measured output value. The feedforward portion of the control phase is treated as "perfect" feedforward control, where the control action is designed to keep the controlled variable exactly at the set point despite dynamic effects from the system [50].

$$G_f = -\frac{G_d}{G_t G_v G_p} \tag{4.5}$$

The dynamic effects of G_t and G_v are neglected in this study and then G_f is estimated as a lead-lag unit. A lead-lag unit is used in this case to estimate the dynamics of the disturbances and process and their effect on the control action. Attempting to use the transfer functions outlined in Figure 4.1 leads to a physically unrealizable controller.

$$G_f = -\frac{K_f(\tau_1 s + 1)}{(\tau_2 s + 1)} \tag{4.6}$$

K_f, τ_1, and τ_2 are adjustable parameters in equation (4.6). The adjustable parameters were tuned using the steps outlined in Seborg et al [50]. Due to the dynamics in this system, offset is not a concern and K_f was adjusted until a reasonable control response was achieved. The optimal value used for K_f in this work was determined to be 0.35. τ_1 and τ_2 were set to zero while a trial and error approach was used to establish an appropriate value for K_f. The controlled variable responds faster to the manipulated variable in this system due to its location downstream of the disturbance variable, so the heuristic approach of $\tau_1/\tau_2 = 0.5$ was used to set an initial value for these two parameters. τ_1 and τ_2 were then slightly fine tuned to .01 and .025, respectively, as the disturbance value was adjusted to establish the controller so that it would minimize large disturbances effectively. The controller action, P_{ff}, is then defined as G_f multiplied by the disturbance in inlet chlorine concentration, D_c.

$$P_{ff} = -\frac{K_f(\tau_1 s + 1)}{(\tau_2 s + 1)} D_c \tag{4.7}$$

The NMPC control law in equations (4.1) through (4.7) is a multi-variable, proportional control law utilizing a receding horizon approach and a dynamic process model. It is based on predicted error generated by the optimization/scheduling layer shown in Figure 4.5. The controller tuning parameters are shown in Table 4.2. To ensure that the slowest dynamics in the system were adequately compensated for, this study used the settling time(t_s) of the demand chlorine concentration control response. It was determined to be 13 hours. Heuristics outlined in Seborg et al. were then used to determine values for the control(M) and prediction(P) horizons [50]. All outputs are weighted equally, so the diagonal elements(q_{ii}) of the output weighting matrix($\boldsymbol{Q}$) are assigned a value of one.

$$
\begin{aligned}
\frac{\frac{t_s}{\triangle t}}{3} < M < \frac{\frac{t_s}{\triangle t}}{2} \\
P = \frac{t_s}{\triangle t} + M
\end{aligned}
\tag{4.8}
$$

Parameter	Value	Units
M	5	hrs
P	24	hrs
q_{ii}	1	
$\triangle u^c_{lb}$	0	gal/hr
$\triangle u^c_{ub}$	1	L/hr
$\triangle u^v_{lb}$	0	L/hr
$\triangle u^v_{ub}$	$30,000$	gal/hr
K^c_c	-0.35	mg/L^2
K^v_c	15	hrs

Table 4.2: MPC model parameters.

4.4.1 Averaging Level Control

The storage tanks in water systems are operated as surge tanks to not only damp out oscillations in the inlet stream, but to provide a constant and predictable pressure to customers. Where downstream flow rates change gradually, water levels can be maintained within specified upper and lower limits, and steady-state mass balances can be satisfied at all times, averaging level control is appropriate and is often employed successfully when conditions warrant [50, 52].

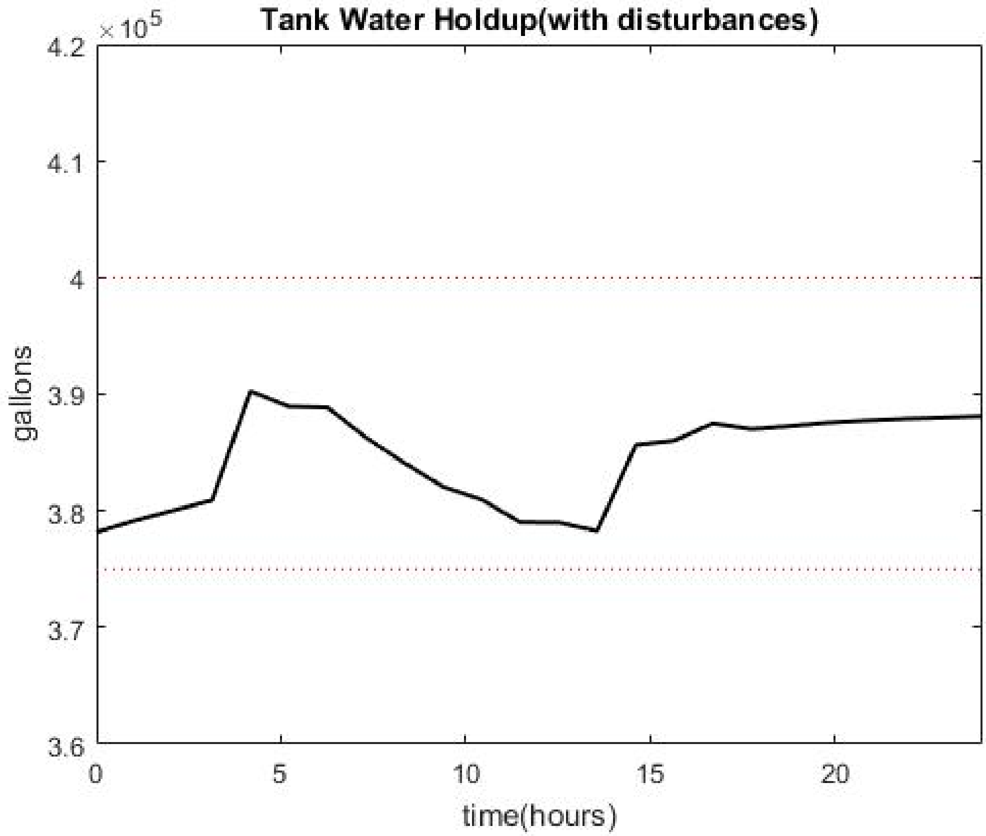

Figure 4.8: Average level control of tank holdup. Red dotted lines represent upper and lower constraints on tank holdup.

Using averaging level control in this system contributes greatly to the systems ability, guided by robust control and optimization, to minimize large disturbances. Figure 4.8 shows the results of averaging level control on the model system, giving the controller flexibility to hold inventory when predictions require it.

4.5 Controller Design Results and Discussion

The NMPC controller described in the previous section was implemented using GAMS and the MATLAB Simulink environment. GAMS performed the optimization and scheduling of pumping action as described in Chapter 3. The remainder of this chapter is dedicated to presenting the results of this work.

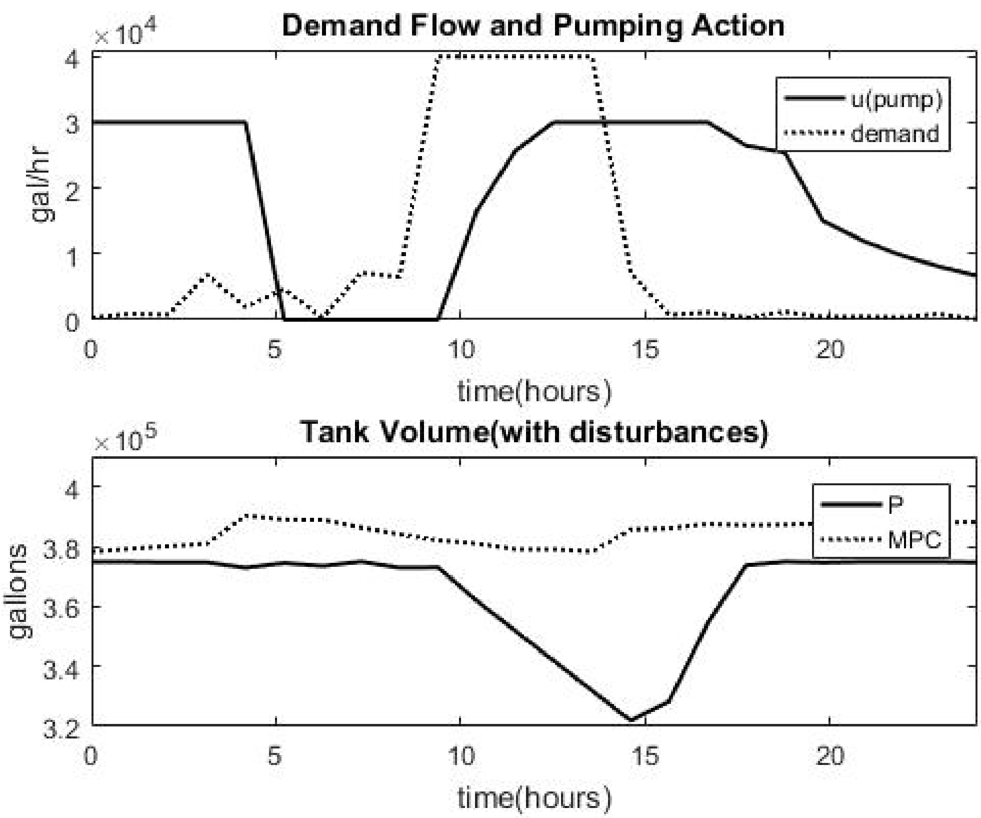

Figure 4.9: Controller action to minimize disturbance on tank holdup. In the bottom plot, MPC is compared to proportional control on tank holdup under the same conditions.

4.5.1 Closed Loop Controller Response

Figure 4.9 shows the control action affecting tank water holdup under large disturbances. The controller provides an immediate and accurate response to a large demand load on the system. Although there is approximately one hour of delay in the system's reaction to the demand, the effect of the large demand on the CV is minimal and the critical tank holdup is maintained. The input curve at the top of Figure 4.9 shows two large control actions: (1)scheduled pumping that was completed to avoid pumping during the peak hours of the day and (2)un-scheduled pumping during peak hours due to closed-loop control attempting to maintain the system within constraints. When compared to closed-loop proportional control under the same conditions, MPC is the clear choice to ensure the effect of disturbances is minimized. Figure 4.9 shows the proportional controller recovering the system to the set point, but the response is delayed for approximately eight hours and it allows the tank holdup level to decrease well below the lower constraint of 375,000 gallons. The military's need for aggressive adherence to the lower constraint on tank holdup means that regulatory control alone is insufficient.

Large disturbances on inlet concentration pose a unique challenge to military water systems. Due to the size of water systems, the distance between the inlet and the CV of concern is usually extensive. Distance and chlorine reaction kinetics combine to create a time delay on the demand chlorine concentration. If a large disturbance on inlet concentration were to occur currently, the majority of the water system would be contaminated before the disturbance was detected. Feedforward control shown in Figure 4.10 demonstrates an effective solution to excessive distur-

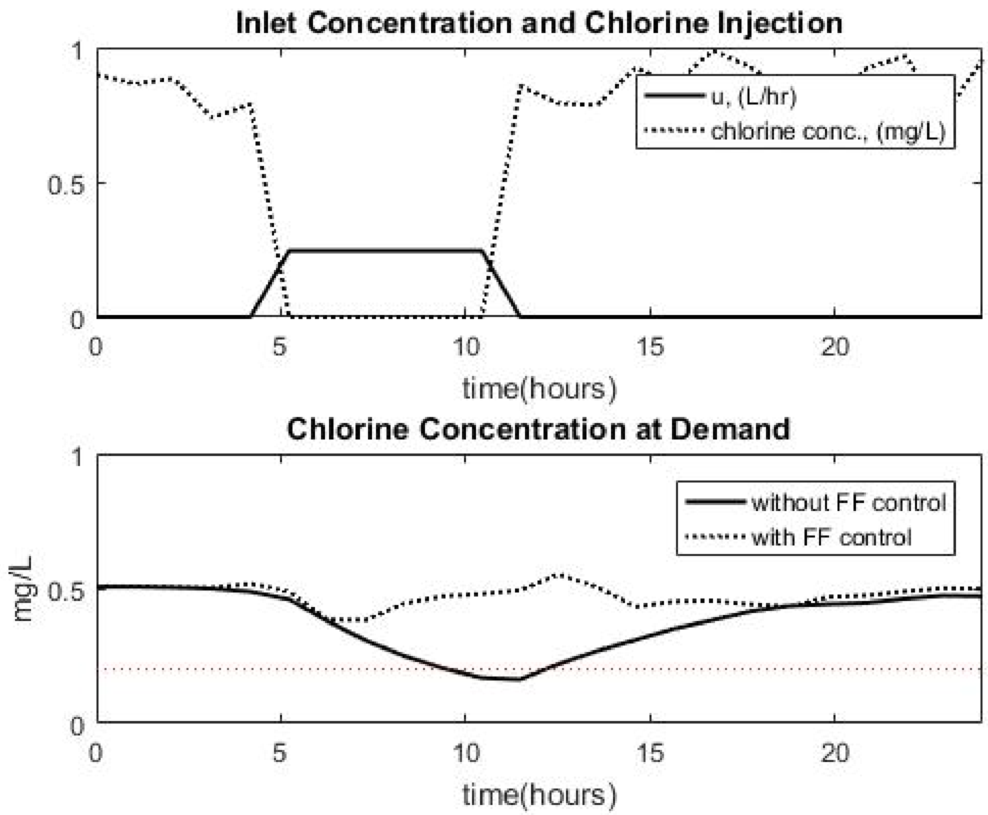

Figure 4.10: Feedforward control response to large disturbances on inlet chlorine concentration and the effect on demand chlorine concentration.

bances. Because the disturbance is recognized immediately by the controller as well as the plant, control action begins to compensate immediately after the disturbance occurs. The CV continues to decrease for at least two hours after compensation for compensation due to the system time delay, but the CV remains well within constraints. Conversely, the CV decreases below the lower chlorine concentration constraint when feedforward control is not employed. Without feedforward control, the system time delay dominates, ensures that the concentration descends below the lower constraint, and spends at least twelve hours re-establishing the steady state.

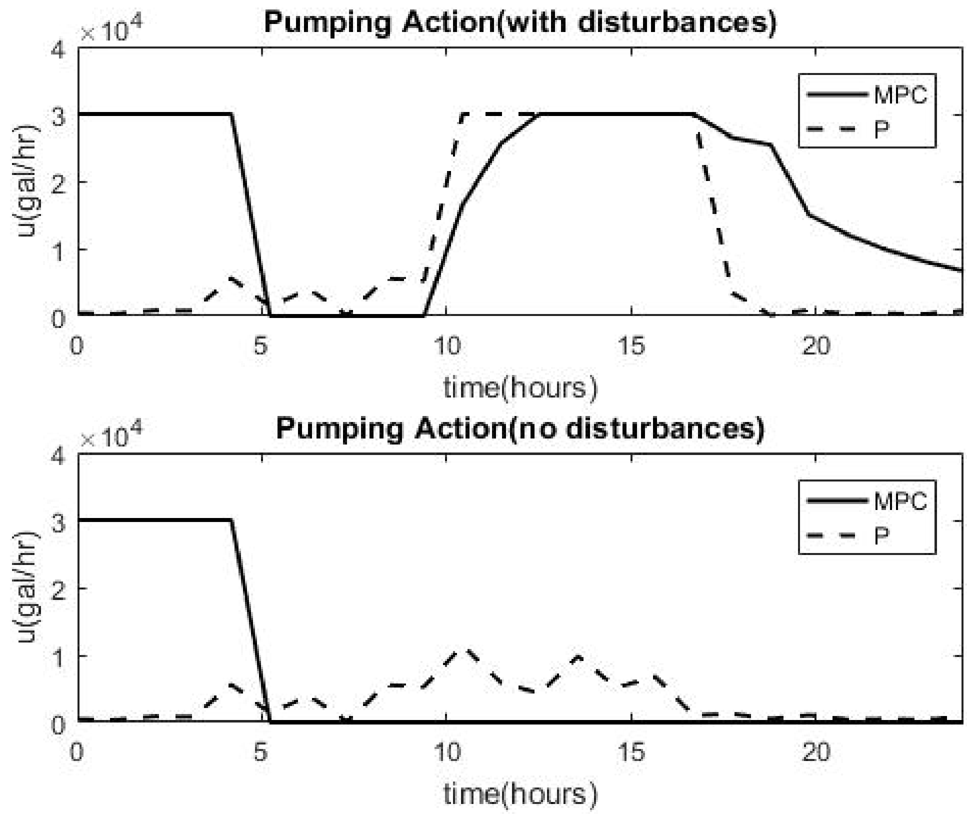

Figure 4.11: Optimized chlorine concentration at node one over a seven day period.

While conserving water and electricity are motivations for this work, reducing costs to the military while maintaining resiliency receive priority when inefficiencies are concerned. Since the majority of the cost of providing potable water to installations is related to pumping water to fill tanks, it follows that any efforts to minimize cost should begin there. As shown in Figure 4.11, the MPC framework outlined earlier in this chapter attempts to pump in a pattern that avoids the more expensive

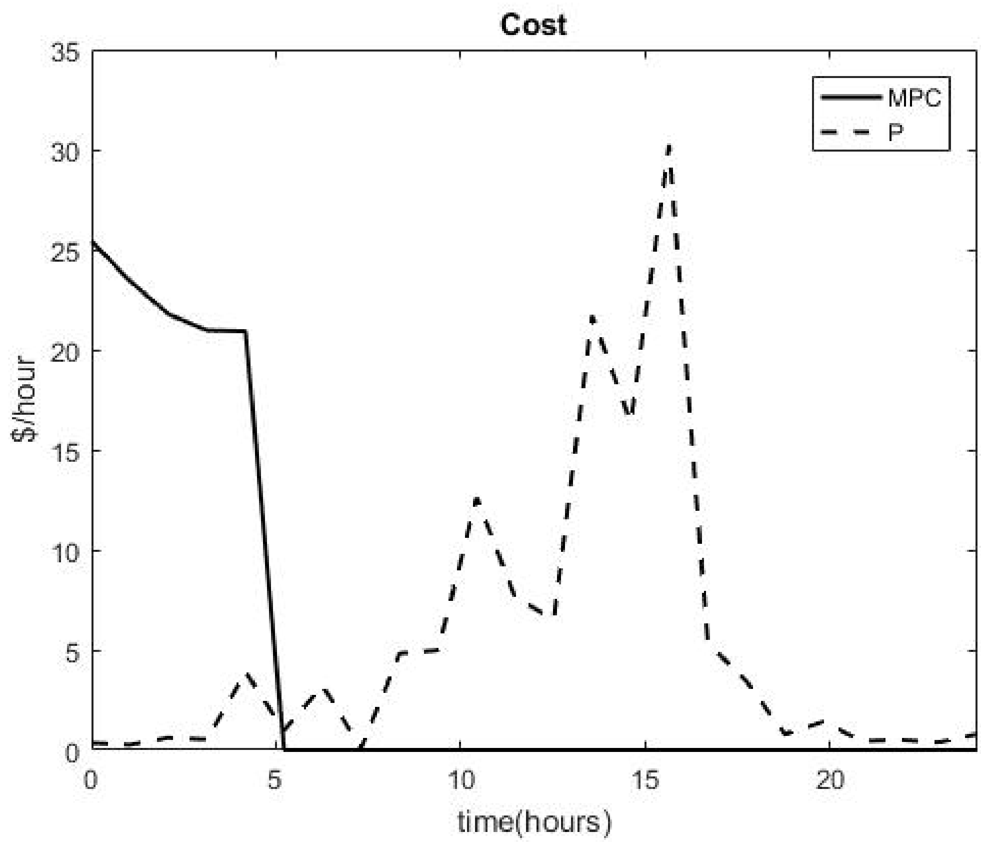

Figure 4.12: Optimized chlorine concentration at node one over a seven day period.

times of the day based on day ahead electricity pricing. Figure 4.11 shows the action of MPC with and without large disturbances present. Without disturbances, the controller will ensure that pumping is accomplished in the most inexpensive manner possible and will only pump during the unfavorable hours of the day if it needs to in order to maintain critical system constraints. Safety and resiliency is prioritized by the controller. Regulatory control alone will also effectively manage tank holdup in the absence of disturbances, but does not discriminate against higher prices in the afternon, leading to excessive cost. Because of its predictive nature, MPC has the effect of having water inventory on hand when large disturbances occur that allow it to respond in a more efficient and inexpensive manner. Regulatory control alone with no predictive capability is at a disadvantage and does not perform as well because it did not store an additional amount of inventory during the more inexpensive times of the day. Figure 4.12 shows the cost comparison of regulatory control and MPC with no disturbances present. A 12% decrease in cost is realized when MPC is implemented. This decrease is realized because the controller manipulates the pumping action based on the cost of electricity and regulatory control does not.

4.6 Conclusion

In conclusion, large disturbances within military water systems can be adequately controlled using nonlinear model predictive control. Due to distance, time delays, time scales, and reaction kinetics, multiple types of control (feedback, feedforward, etc.) should be employed in the regulatory layer to compensate for disturbances effectively while maintaining constraints for safety and resiliency. As discussed, water system modeling is hindered by the existence of different time scales of phenomena within the system. The solution of this controller follows the process control hierarchical structure in Figure 1.4, employing the regulatory control layer to manage the fast dynamics of the system while the supervisory controller developed in this chapter effectively managed the slow dynamics [56]. The NMPC framework outlined lowers costs and reduces waste, while improving resiliency and safety.

Chapter 5

Smart Water

5.1 Introduction

This chapter proposes the integration of high resolution water system data, accurate modeling, and comprehensive system observation tools with robust optimization and control. International Business Machines(IBM) corporation has developed a software tool that gives users, municipalities, and technicians insight into usage patterns, leaks, and fraud through the leveraging of high resolution system data [6]. Further, their Digital Delta initiative has transformed water management in the flood prone Netherlands by using extensive data to integrate water treatment with flood control, weather patterns, sewage, and drainage. CH2M corporation uses similar approaches using metered data, when available, to assist local governments in managing water resources [5]. In both cases, these companies consult around the world to help municipalities improve efficiency and reduce waste by improving access to and visualization of data that improves the decision making process. Although these efforts are noble and in many cases have contributed to remarkable progress, the decision making approaches they support are still heuristics based and subject to human error. This chapter's goal is to propose a smart water framework for the military that leverages large scale metered data with robust optimization and control.

5.1.1 Literature Review

Smart manufacturing has provided efficiencies to a variety of industries by creating synergy between the wealth of system data available through advanced sensor employment and relatively inexpensive yet powerful network and computer processing capabilities [19, 27]. A recent paper by Korambath, et al. describes a framework for smart manufacturing that integrates advanced sensors, optimization, and a robust network to dramatically enhance efficiency in steam methane reformers [30]. Other recent applications include vehicle manufacturing, sensors, healthcare, and supply chain management [32].

Although there are numerous examples of integrated technologies helping manufacturers gain unprecedented real-time control and optimization of energy, productivity, and costs across factories, there are very few instances where this framework has been applied to water networks [3]. Two papers on the topic discuss the exploitation of large scale smart metered water use data in a knowledge management context to make more informed decisions while operating water networks, enough to label them "smart water" networks [31, 53]. Although a step in the right direction, these advancements do not include the use of optimization and control. A knowledge gap exists in the literature with respect to integrating metered data, sensors, knowledge platforms, optimization, and control into municipal water networks, analogous to the body of work that exists for smart manufacturing. This chapter seeks to demonstrate the future potential of an intelligent water construct.

5.1.2 Motivation and Scope

The motivation to dramatically increase the efficiency of municipal and military water networks shares the same core principles as the motivation for smart manufacturing. The United States government through the Department of Energy(DOE) recently established the Smart Manufacturing Leadership Coalition and the Smart Manufacturing Innovation Institute to revolutionize manufacturing, increase competitiveness, and greatly improve efficiency. Providing potable water is also energy intensive and water is a vital resource that is becoming endangered [36]. The importance of water to human life and the stress it currently experiences worldwide requires a disruptive technology that goes well beyond current practices. Arguably a substantial consumer of water resources to support training, life support, and maintenance, the military has a role to play in advancing technology with respect to managing municipal water resources.

5.2 A Framework for Change: Smart Water

To propel the idea of Smart Water management into the future we should resist the past practice of making progress in isolated silos of knowledge. Instead, improvements in managing water networks should be complimentary to each other and a synergy realized through integration. As noted earlier, much has been written about modeling, optimization, and some control of critical elements of water systems. These ideas provide some progress towards making our water systems more efficient, but with the restrictions of operating without knowledge of other areas. Current operations of military municipal water systems are managed by a supervisory control and data acquisition(SCADA) type visualization tool. The tool allows for basic visualization of tank holdup and indicates whether pumps are activated. The tool does not manipulate MVs or consolidate large amounts of data for analysis; it simply provides an interface for operators to visualize the system in its basic form.

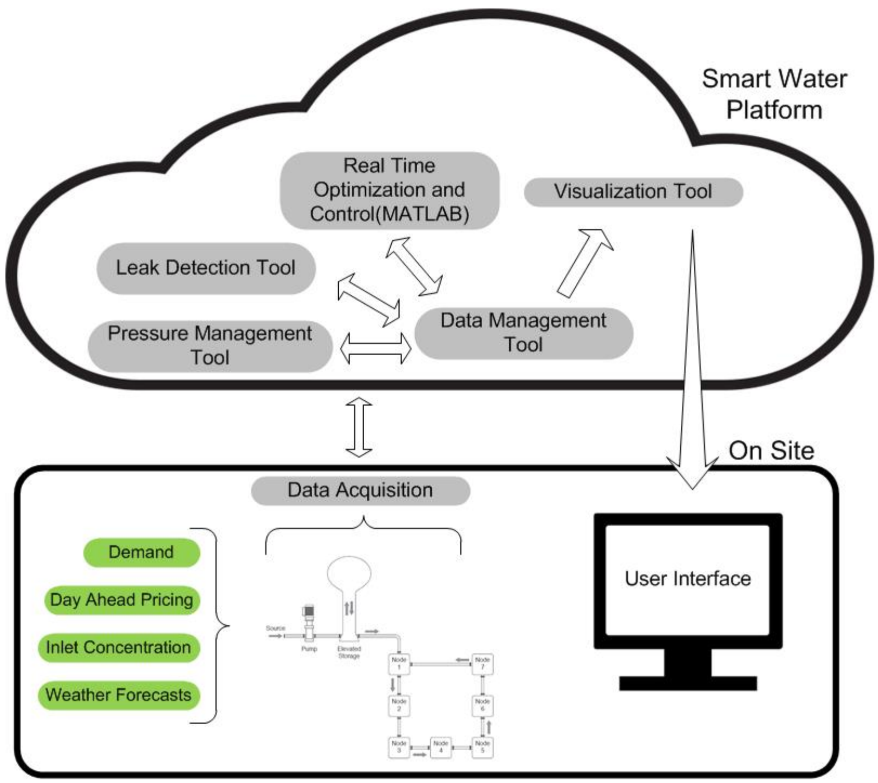

Figure 5.1: Framework for improved efficiency by integrating optimization and control with improved sensors and large scale data acquisition.

Figure 5.1 depicts the Smart Water framework that can potentially change that. Similar to Smart Manufacturing, synergy can be realized when the individual benefits of advanced sensors, modeling, optimization, control, and data visualization are integrated to create a concentrated effort focused on improvement. Water system demand, inlet concentration, weather forecasts, and day ahead electricity pricing serve as disturbances to the system providing potable water to customers at the demand nodes. Advanced sensors are implemented in the system to gather high resolution data on chlorine concentration, pressure, tank holdup, and inlet chlorine concentration. Data is acquired and transmitted over a network infrastructure to be used by the Smart Water platform. Existing tools for leak detection and pressure management continue to operate but provide data for operator decision making through the visualization tool. Implementing advanced sensors and providing the data to the Smart Water platform allows for the effective use of optimization and control algorithms. The algorithms utilize real time data, observed by operators through the visualization tool, to provide control inputs to MVs, keeping CVs within operator's specified limits and state and federal water safety laws and regulations.

5.3 Conclusion

High resolution data acquired by affordable sensors and integrated into an optimization/control/visualization framework will increase efficiency of water systems and reduce costs. The previous chapters of this dissertation demonstrated success in reducing costs and water usage on an experimental basis without real-time data and the other benefits of a Smart Water platform. An integrated approach like the one described above as Smart Water will potentially make even greater improvements on waste and energy consumption than what was demonstrated in the previous chapters. Further study and implementation of the Smart Water platform should be conducted to investigate potential benefits.

Chapter 6

Conclusions and Recommendations

6.1 Summary of Work Completed

This chapter highlights the work completed and key conclusions on the investigation of military water system modeling, optimization, and control. The sections that follow will cover the contributions and findings.

6.1.1 Water System Modeling

A distributed equation based model was developed in Chapter 2. Building on the work of Rossman et al., the model accounts for the unique characteristics and constraints of military water systems and is based on a portion of the system at Fort Carson, CO. A set of partial differential equations, ordinary differential equations, and algebraic material balances describe water flow and the evolution of chlorine concentration throughout the pipe network. For efficient solving, the partial differential equations were discretized in axial space and time. The model was validated for accuracy with data gathered from Fort Carson, CO. Sensitivity analysis was conducted to determine the most influential system variable on the cost of system operation. Analysis determined that, due to the overwhelming cost of water conveyance, reducing tank water holdup would have the greatest impact on overall cost. After many unsuccessful tries, it was determined that the time step for modeling was incorrect.

An adaptation of the Courant condition was used to determine a time step that ensured convergence of the model.

6.1.2 Optimization of Water System Operation

Using the model developed in Chapter 2, this chapter features a nonlinear optimization program (NLP) to reduce the cost of pumping based on day ahead electricity pricing while reducing tank holdup and meeting system constraints. The CONOPT solver in the GAMS optimization software package was used and it took 13 minutes solve the problem consisting of over 17,000 variables and equations. The NLP takes into account unique military installation demand patterns and resiliency constraints to reduce the cost of providing water by 10% annually. The program is able to save money by directing water pumping, the most expensive portion of the water system operation, to the hours of the day when electricity is the least expensive. Further, the system reduces tank holdup by 10%, greatly reducing cost because only water that is needed is being treated, pumped, and stored. Reducing excess holdup also drastically reduces the potential that the water would be flushed, or wasted, after its chlorine level decreases below the minimum due to excessive residence time.

6.1.3 Nonlinear Model Predictive Control for Disturbance Minimization

To improve upon the performance of the NLP developed in Chapter 3, a supervisory controller was developed. The optimization layer alone does not perform well under potentially large disturbances that exist in military systems. To maintain the advantage of cost savings gained by the NLP and minimize large disturbances, a supervisory nonlinear model predictive control algorithm is developed and coupled with the optimization/scheduling layer. The MIMO MPC structure contains two control actions on manipulated variables that compensate for fast dynamics within the system: (1)feedback control to manage tank holdup and (2)feedforward control to compensate for large disturbances on inlet concentration and negate their effects on customers at the demand side. Feedforward control action is essential when dealing with disturbances on inlet concentration; the distance and time delay between disturbance and affected CV yields feedback control ineffective. Using models outlined in Chapter 2 to enhance predictive capability, the controller provides rapid and effective control action to minimize disturbances and increase resiliency, while maintaining substantial cost and energy savings.

6.2 Recommendations for Future Work

The following sections outline ideas for future work that the author intends to pursue.

6.2.1 Data Gathering and Model Development

Although the model in this work appears to be accurate through validation and serves as a great platform for discussion, optimization, and control, it is based on a relatively limited data set. When compared to plant processes like distillation columns, heat exchangers, or reactors that are fitted with sensors gathering constant streams of data, military and civilian water systems are deficient. In fact, most decisions in water systems today are made using an heuristic approach. Without large scale, extensive water data the accuracy of empirical models could be called into question. Because any future control implementation on water systems to save water and capital will rely on ever more accurate models, data gathering should be prioritized. Improving models through water data is a future line of effort to improve military water systems. Due to the nonlinear nature of the system, step-response modeling is likely the best alternative to current practices.

6.2.2 Smart Water Integration

The rise of smart manufacturing proves the synergy between big data, robust monitoring, optimization, and control and its ability to fundamentally transform cost savings and efficiency in almost any industry. Recent achievements in this area have inspired efforts to conduct similar work in the water industry. IBM's Intelligent Water platform, for instance, is similar to manufacturing with respect to big data and robust monitoring through enhanced computer capability. To be transformational in the water industry, they must include real time optimization and robust control. With the slow but gradual introduction of useful sensor technology for water systems, big water data will finally become reality. With plentiful data for monitoring and analysis, models can be made significantly more accurate and as plant conditions change these models can be reformulated. Highly accurate models lead to excellent optimization and control results, and these efforts should begin integrating optimization and control into the system architecture now. Future work of the author will be focused on enhanced sensor deployment, data gathering and storage, and integration of said data into an intelligent framework that exploits the power of modeling, optimization, and control to save water and capital.

6.2.3 Process Intensification

Water is one of our more inexpensive commodities and arguably grossly undervalued. Low prices leave no social motivation to conserve and a tendency to apply much needed private and public funds to other areas. As population increases lead to water stress over the coming decades, innovation in the water sector will be motivated by the need to preserve this essential resource. To make military water systems substantially more efficient, secure, resilient, and inexpensive, a systems level process intensification effort should be undertaken. Process intensification has succeeded in improving countless industrial processes and combined with the tools outlined in this dissertation, could provide substantial improvements [17].

Appendix

This appendix includes GAMS code referenced in Chapter 3, the nonlinear program that optimizes the military municipal water system for reduced water holdup and pumping cost based on day ahead electricity pricing. Secondary effects of reduced holdup and cost include lower energy consumption and reduced emissions.

```
$onecho > taskin.txt
dset=t rng=a3:a170 rdim=1
par=F rng=Standard!a3:b170 rdim=1
par=rate rng=Standard!e3:f170 rdim=1
par=Co rng=Standard!i3:j170 rdim=1
$offecho

$call gdxxrw.exe import8.xlsx @taskin.txt
$gdxin import8.gdx

* sets are stated for time, pipe designation, and discretized location along each pipe

Sets
        t hours /1*72/
        k links /3*9/
        x length along pipe /1*10/;


Scalar
        Coo initial chlorine concentration in tank (mg per liter) /.5/
        Cmin minimum concentration of chlorine system wide (mg per liter) /.2/
        Cmax maximum concentration of chlorine system wide (mg per liter) /1/
        vmax maximum tank volume /500000/
        kt reaction rate constant (hr-1) /.217673/
        kb bulk reaction rate constant (hr-1) /.0229167/
        gal conversion from gal to ft3 /.133681/
        r radius of pipe(inches) /5/
        A area of pipe (ft^2) /.545/
        head height of water (ft) /120/
        dL1 length of pipe 1 (ft) /1484/
        dL2 length of pipe 2 (ft) /1238/

* loading information from excel file accessed by gdxin operation

*F(t) is demand flow
Parameter F(t)
$load F
*rate(t) is the day ahead price of electricity
Parameter rate(t)
$load rate
*Co(t) is the inlet chlorine concentration
Parameter Co(t)
$load Co
$gdxin
display F
display rate
display Co

* length of pipes, in feet, leading to demand

Parameter
        dL(k) /3 648
               4 344
               5 364
               6 202
               7 214
               8 180
```

```
Parameter dt(t)time step in hours;
            dt(t) = .0153846;

Parameter v0 initial amount of water in the tank (liters);
   v0 = 387500;

Parameter c0 initial chlorine concentration in the tank (mg per liter);
  c0 = .5;

positive variables C(t,x) *chlorine concentration from inlet to tank
                   Cd(t,x) *chlorine concentration from tank to demand
                   Cn(t,k,x) *chlorine concentration in pipes near demand
                   CTank(t) *chlorine concentration in tank
                   v(t) *tank holdup
                   q(t) *volumetric flow rate from inlet to tank
                   qd(t) *volumetric flow rate from tank to demand nodes
                   qn(t,k) *volumetric flow rate between various demand nodes
                   cjunction1(t) *chlorine concentration at node 1
                   cjunction2(t) *chlorine concentration at node 2
                   cjunction3(t) *chlorine concentration at node 3
                   cjunction4(t) *chlorine concentration at node 4
                   cjunction5(t) *chlorine concentration at node 5
                   cjunction6(t) *chlorine concentration at node 6
                   cjunction7(t) *chlorine concentration at node 7;

variables

         cost(t)
         totalcost;

Equations

pumpingtotalcost
pumpingcost(t)
Waterbalentry(t)
Waterbal(t,x)
Waterbalexit(t)
Waterbaldentry(t)
Waterbald(t,x)
Waterbaldexit(t)
Waterbalnentry3(t)
Waterbalnentry4(t)
Waterbalnentry5(t)
Waterbalnentry6(t)
Waterbalnentry7(t)
Waterbalnentry8(t)
Waterbalnentry9(t)
Waterbaln(t,k,x)
Waterbalnexit(t,k)
Waterbaltank(t)
Tankbal(t)
Waterbal_initial(t)
Chlorinebal_initial(t)
junctionbalance1(t)
junctionbalance2(t)
junctionbalance3(t)
junctionbalance4(t)
junctionbalance5(t)
junctionbalance6(t)
junctionbalance7(t)
```

```
*Initial guess and condtions, used to establish a good initial point for optimization

CTank.l(t) = .5;
v.l(t) = 376000;
Cn.l(t,k,x) = .6;
C.l(t,x) = .9;
Cd.l(t,x) = .6;
q.l(t) = 0;
qn.l(t,k)=500;
qd.l(t) = 1000;

*Initial conditions

nodeic1(t,k,x).. Cn('43','3','1') =e= .4340;
c1(t,x).. C('1','10') =e= .9;
qic(t).. q('43') =e= 25398;
vic(t).. v('43') =e= 388609;

*water quality equations
Waterbal_initial(t)$(ord(t) eq 1).. v(t) =e= v0;
Chlorinebal_initial(t)$(ord(t) eq 1).. CTank(t) =e= c0;

*pipe leading to tank
Waterbalentry(t)$(ord(t) gt 1)..C(t,'1')-C(t-1,'1') =e= (((-q(t)*gal/A)*(C(t,'1')-Co(t»
))/dL1-kt*C(t,'1')))*dt(t);
Waterbal(t,x)$(ord(x) gt 1 and ord(x) lt 10 and ord(t) gt 1)..C(t,x)-C(t-1,x) =e= (((-»
q(t)*gal/A)*(C(t,x)-C(t,x-1))/dL1-kt*C(t,x)))*dt(t);
Waterbalexit(t)$(ord(t) gt 1)..C(t,'10')-C(t-1,'10') =e= (((-q(t)*gal/A)*(C(t,'10')-C(»
t,'9'))/dL1-kt*C(t,'10')))*dt(t);

*tank
Tankbal(t)$(ord(t) gt 1)..v(t)*CTank(t)-v(t)*CTank(t-1) =e= ((q(t)*C(t,'10')-qd(t)*CTa»
nk(t)-v(t)*kb*CTank(t)))*dt(t);
Waterbaltank(t)$(ord(t) gt 1).. v(t)-v(t-1)=e=(q(t)-2*qd(t))*dt(t);

*pipes to demand
Waterbaldentry(t)$(ord(t) gt 1)..Cd(t,'1')-Cd(t-1,'1') =e=(((-qd(t)*gal/A)*(Cd(t,'1')-»
CTank(t))/dL2-kt*Cd(t,'1')))*dt(t);
Waterbald(t,x)$(ord(x) gt 1 and ord(x) lt 10 and ord(t) gt 1)..Cd(t,x)-Cd(t-1,x) =e= (»
((-qd(t)*gal/A)*(Cd(t,x)-Cd(t,x-1))/dL2-kt*Cd(t,x)))*dt(t);
Waterbaldexit(t)$(ord(t) gt 1)..Cd(t,'10')-Cd(t-1,'10') =e= (((-qd(t)*gal/A)*(Cd(t,'10»
')-Cd(t,'9'))/dL2-kt*Cd(t,'10')))*dt(t);

*network pipes
Waterbalnentry3(t)$(ord(t) gt 1)..Cn(t,'3','1')-Cn(t-1,'3','1') =e= (((-qn(t,'3')/A)*(»
Cn(t,'3','1')-cjunction1(t))/dL('3')-kt*Cn(t,'3','1')))*dt(t);
Waterbalnentry4(t)$(ord(t) gt 1)..Cn(t,'4','1')-Cn(t-1,'4','1') =e= (((-qn(t,'4')/A)*(»
Cn(t,'4','1')-Cn(t,'3','10'))/dL('4')-kt*Cn(t,'4','1')))*dt(t);
Waterbalnentry5(t)$(ord(t) gt 1)..Cn(t,'5','1')-Cn(t-1,'5','1') =e= (((-qn(t,'5')/A)*(»
Cn(t,'5','1')-Cn(t,'4','10'))/dL('5')-kt*Cn(t,'5','1')))*dt(t);
Waterbalnentry6(t)$(ord(t) gt 1)..Cn(t,'6','1')-Cn(t-1,'6','1') =e= (((-qn(t,'6')/A)*(»
Cn(t,'6','1')-Cn(t,'5','10'))/dL('6')-kt*Cn(t,'6','1')))*dt(t);
Waterbalnentry7(t)$(ord(t) gt 1)..Cn(t,'7','1')-Cn(t-1,'7','1') =e= (((-qn(t,'7')/A)*(»
Cn(t,'7','1')-Cn(t,'6','10'))/dL('7')-kt*Cn(t,'7','1')))*dt(t);
Waterbalnentry8(t)$(ord(t) gt 1)..Cn(t,'8','1')-Cn(t-1,'8','1') =e= (((-qn(t,'8')/A)*(»
Cn(t,'8','1')-Cn(t,'7','10'))/dL('8')-kt*Cn(t,'8','1')))*dt(t);
Waterbalnentry9(t)$(ord(t) gt 1)..Cn(t,'9','1')-Cn(t-1,'9','1') =e= (((-qn(t,'9')/A)*(»
Cn(t,'9','1')-Cn(t,'8','10'))/dL('9')-kt*Cn(t,'9','1')))*dt(t);
Waterbaln(t,k,x)$(ord(x) gt 1 and ord(x) lt 10 and ord(t) gt 1)..Cn(t,k,x)-Cn(t-1,k,x)»
 =e= (((-qn(t,k)/A)*(Cn(t,k,x)-Cn(t,k,x-1))/dL(k)-kt*Cn(t,k,x)))*dt(t);
```

```
*node balances, where demand flow is different at each node as noted by the multiplyin»
g factor * F(t)
junctionbalance1(t)..F(t)*.15 =e= qd(t)+qn(t,'9')-qn(t,'3');
junctionbalance2(t)..F(t)*.10 =e= qn(t,'3')- qn(t,'4');
junctionbalance3(t)..F(t)*.15 =e= qn(t,'4')- qn(t,'5');
junctionbalance4(t)..F(t)*.25 =e= qn(t,'5')- qn(t,'6');
junctionbalance5(t)..F(t)*.05 =e= qn(t,'6')- qn(t,'7');
junctionbalance6(t)..F(t)*.15 =e= qn(t,'7')- qn(t,'8');
junctionbalance7(t)..F(t)*.15 =e= qn(t,'8')- qn(t,'9');


*node boundary conditions

cjunctionbc1(t)..cjunction1(t)* (qn(t,'3')+F(t)*.15) =e= qn(t,'9')*Cn(t,'9','10')+ Cd(»
t,'10')*qd(t);

*pumping constraints

pumpingconstraint1(t)$(ord(t) gt 10 and ord(t) lt 16)..q(t) =e= 0;
pumpingconstraint3(t)$(ord(t) gt 59 and ord(t) lt 64)..q(t) =e= 0;
pumpingamountconstraint(t)..q(t) =l= 30000;

*cost constraints(objective function)
pumpingcost(t)..cost(t) =e= (.746*q(t)*head*rate(t))/(3960*.9*.9);
pumpingtotalcost..totalcost =e= sum((t), cost(t));

*Lower bounds
CTank.lo(t) =  .5;
v.lo(t) = 320000;
Cn.lo(t,k,x) = Cmin;
C.lo(t,x) = .5;
Cd.lo(t,x) = 0.4;

*Upper bounds
CTank.up(t) =  Cmax;
Cn.up(t,k,x) = Cmax;
C.up(t,x) = Cmax;
Cd.up(t,x) = Cmax;
v.up(t) = 398000;
qn.up(t,k) = 50000;


model PartIII /all/;
options NLP = conopt;
solve PartIII using NLP minimizing totalcost;
execute_unload 'data.gdx', q.l, v.l, Cd.l, qn.l, qd.l, C.l, Cn.l;
execute 'gdxxrw.exe data.gdx var=Cn.L var=q.l var=v.l var=Cd.l var=qn.l var=qd.l var=C»
.l'
display q.l, CTank.l, Cn.l, v.l, Cd.l, qn.l, qd.l, C.l, cost.l, totalcost.l;
```

```
file mfile1 / C:\Users\cmj696\Documents\Research\Papers\Feedforward Control\carson72hr»
ffdata.m/
put mfile1;
mfile1.nd=3;
mfile1.pw=67500;
mfile1.pc=8;

put '% Total Cost/objective'/
put 'Total Cost = '
put totalcost.l
put ';'//

put '% v aka volume of water in tank'/
put 'volume = ['
loop(t, put v.l(t); put/)
put '];'//

put '% Cost aka cost for pumping each hour'/
put 'cost = ['
loop(t, put cost.l(t); put/)
put '];'//

put '% qd aka flow from tank to demand'/
put 'qd = ['
loop(t, put qd.l(t);put/)
put '];'//

put '% q aka flow from pump to tank'/
put 'q = ['
loop(t, put q.l(t);put/)
put '];'//

put '% F aka demand flow'/
put 'F = ['
loop(t, put F(t);put/)
put '];'//

put '% rate aka electricity rate'/
put 'rate = ['
loop(t, put rate(t);put/)
put '];'//

put '% Co aka initial concentration at source'/
put 'Co = ['
loop(t, put Co(t);put/)
put '];'//

put '% Cn aka concentration at node 1'/
put 'Cn = ['
loop(t, put Cn.l(t,'3','1');put/)
put '];'//

put '% C1 aka concentration just prior to tank'/
put 'C1 = ['
loop(t, put C.l(t,'10');put/)
put '];'//

put '% qd aka flow from tank to demand'/
put 'qd = ['
loop(t, put qd.l(t);put/)
```

Bibliography

[1] Drinking water requirements for states and public water systems. Online: accessed 2-15-2017.

[2] Ensuring a sustainable future: An energy management guidebook for wastewater and water utilities. Online: accessed 12-31-2015.

[3] Smart manufacturing: Transforming american manufacturing with information technology. Online: accessed 1-29-2017.

[4] Strategies for saving energy at public water systems(epa report 816-f-13-004). Online: accessed 12-31-2015.

[5] Water. Online: accessed 1-28-2017.

[6] Water management software with analytics for improved infrastructure and operations. Online: accessed 1-28-2017.

[7] Promoting technology innovation for clean and safe water: Water technology innovation blueprint-version 2. U.S. Environmental Protection Agency Office of Water, October 2014.

[8] Elvis Ahmetović and Ignacio E. Grossmann. Global superstructure optimization for the design of integrated process water networks. *AIChE journal*, 57(2):434–457, 2011.

[9] Paul F Boulos, Tom Altman, Pierre-Antoine Jarrige, and Francois Collevati. An event-driven method for modelling contaminant propagation in water networks. *Applied mathematical modelling*, 18(2):84–92, 1994.

[10] Nicole C. Brambila. Cities wasted nearly 300m gallons of water. *Amarillo Globe-News*, 4 July 2014.

[11] MA Brdys, T Chang, and K Duzinkiewicz. Intelligent model predictive control of chlorine residuals in water distribution systems. *Proc. ASCE Water Resource Engineering and Water Resources Planning and Management*, pages 391–401, 2001.

[12] Mietek A Brdys, Tao Chang, Kazimierz Duzinkiewicz, and Wiktor Chotkowski. Hierarchical control of integrated quality and quantity in water distribution systems. In *Procs. ASCE 2000 Joint Conference on Water Resources Engineering and Water Resources Planning and Management*, 2000.

[13] Coleman Brosilow and Babu Joseph. *Techniques of model-based control*. Prentice Hall Professional, 2002.

[14] T Chang, MA Brdys, and K Duzinkiewicz. Quantifying uncertainties for chlorine residual control in drinking water distribution systems,. *Proc. ASCE World Water and Environmental Resources*, pages 28–37, 2003.

[15] T Chang, MA Brdys, and K Duzinkiewicz. Decentralized robust model predictive control of chlorine residuals in drinking water distribution systems. In *Proceedings of World Water and Environmental Resources Congress, World Water*

and Environmental Resources Congress and Related Symposia (eds. Paul Bizier and Paul DeBarry), pages 23–26, 2004.

[16] Richard Courant, Kurt Friedrichs, and Hans Lewy. On the partial difference equations of mathematical physics. *IBM journal*, 11(2):215–234, 1967.

[17] Stefano Curcio. Process intensification in the chemical industry: A review. *Sustainable Development in Chemical Engineering Innovative Technologies*, pages 95–118, 2013.

[18] Dataport. *Water demand data gathered on site*. Pecan Street Inc., Austin, TX, 2016.

[19] Jim Davis, Thomas Edgar, James Porter, John Bernaden, and Michael Sarli. Smart manufacturing, manufacturing intelligence and demand-dynamic performance. *Computers & Chemical Engineering*, 47:145–156, 2012.

[20] M Drewa, MA Brdys, and A Ciminski. Model predictive control of integrated quantity and quality in drinking water distribution systems. In *Procs. 8th International IFAC Symposium on Dynamics and Control of Process Systems*, 2007.

[21] Arne Drud. CONOPT: A GRG code for large sparse dynamic nonlinear optimization problems. *Mathematical Programming*, 31(2):153–191, 1985.

[22] K Duzinkiewicz, MA Brdys, and T Chang. Hierarchical model predictive control of integrated quality and quantity in drinking water distribution systems. *Urban Water Journal*, 2(2):125–137, 2005.

[23] Andrew R Fishbein. Public water energy efficiency. Journal of Science Policy and Governance, 6 2014.

[24] Dominic Chwan Yee Foo. State-of-the-art review of pinch analysis techniques for water network synthesis. *Industrial & Engineering Chemistry Research*, 48(11):5125–5159, 2009.

[25] Nick Hallale. A new graphical targeting method for water minimisation. *Advances in Environmental Research*, 6(3):377–390, 2002.

[26] Elisabeth M Jenicek, Noah W Garfinkle, Laura E Curvey, Michael P Case, Marianne Choi, and Annette L Stumpf. Methods of estimating water end use at us army installations. *Journal: American Water Works Association*, 108(2), 2016.

[27] Hyoung Seok Kang, Ju Yeon Lee, SangSu Choi, Hyun Kim, Jun Hee Park, Ji Yeon Son, Bo Hyun Kim, and Sang Do Noh. Smart manufacturing: Past research, present findings, and future directions. *International Journal of Precision Engineering and Manufacturing-Green Technology*, 3(1):111–128, 2016.

[28] Ramkumar Karuppiah and Ignacio E Grossmann. Global optimization for the synthesis of integrated water systems in chemical processes. *Computers & Chemical Engineering*, 30(4):650–673, 2006.

[29] Michael Kiparsky, David L Sedlak, Barton H Thompson Jr, and Bernhard Truffer. The innovation deficit in urban water: the need for an integrated perspec-

tive on institutions, organizations, and technology. *Environmental engineering science*, 30(8):395–408, 2013.

[30] Prakashan Korambath, Jianwu Wang, Ankur Kumar, Jim Davis, Robert Graybill, Brian Schott, and Michael Baldea. A smart manufacturing use case: Furnace temperature balancing in steam methane reforming process via kepler workflows. *Procedia Computer Science*, 80:680–689, 2016.

[31] Seung Won Lee, Sarper Sarp, Dong Jin Jeon, and Joon Ha Kim. Smart water grid: the future water management platform. *Desalination and Water Treatment*, 55(2):339–346, 2015.

[32] Yong Lin, Petros Ieromonachou, and Wenxian Sun. Smart manufacturing and supply chain management. In *Logistics, Informatics and Service Sciences (LISS), 2016 International Conference on*, pages 1–5. IEEE, 2016.

[33] M.A. Maupin, J.F. Kenny, S.S. Hutson, J.K. Lovelace, N.L. Barber, and K.S. Linsey. Estimated use of water in the united states in 2010. *U.S. Geological Survey Circular*, 1405, 2014.

[34] M.A. Maupin, J.F. Kenny, S.S. Hutson, J.K. Lovelace, N.L. Barber, and K.S. Linsey. Estimated use of water in the united states in 2010. U.S. Geological Survey Circular 1405, 2014.

[35] Office of Water. Strategies for saving energy at public water systems. *U.S. Environmental Protection Agency*, July 2014.

[36] Taikan Oki and Shinjiro Kanae. Global hydrological cycles and world water resources. *science*, 313(5790):1068–1072, 2006.

[37] LE Ormsbee, LS Reddy, and DV Chase. Comparison of three nonlinear control algorithms for the optimal operation of water supply pumping systems. In *Integrated computer applications in water supply (vol. 1)*, pages 259–271. John Wiley & Sons, Inc., 1994.

[38] Lindell E Ormsbee and Kevin E Lansey. Optimal control of water supply pumping systems. *Journal of Water Resources Planning and Management*, 1994.

[39] Marios M Polycarpou, James G Uber, Zhong Wang, Feng Shang, and Mietek Brdys. Feedback control of water quality. *Control Systems, IEEE*, 22(3):68–87, 2002.

[40] T Devi Prasad and Nam-Sik Park. Multiobjective genetic algorithms for design of water distribution networks. *Journal of Water Resources Planning and Management*, 2003.

[41] S Joe Qin and Thomas A Badgwell. A survey of industrial model predictive control technology. *Control engineering practice*, 11(7):733–764, 2003.

[42] James Blake Rawlings and David Q Mayne. *Model predictive control: Theory and design*. Nob Hill Pub., 2009.

[43] RE Rosenthal. GAMS: A users guide, 2014.

[44] Lewis A Rossman and Paul F Boulos. Numerical methods for modeling water quality in distribution systems: A comparison. *Journal of Water Resources planning and management*, 122(2):137–146, 1996.

[45] Lewis A Rossman, Paul F Boulos, and Tom Altman. Discrete volume-element method for network water-quality models. *Journal of Water Resources Planning and Management*, 119(5):505–517, 1993.

[46] Lewis A Rossman, Robert M Clark, and Walter M Grayman. Modeling chlorine residuals in drinking-water distribution systems. *Journal of environmental engineering*, 120(4):803–820, 1994.

[47] Lewis A Rossman, James G Uber, and Walter M Grayman. Modeling disinfectant residuals in drinking-water storage tanks. *Journal of environmental engineering*, 121(10):752–755, 1995.

[48] Jeff Sandison. Controlling chlorination in drinking water: water and waste water. *IMIESA*, 31(2):32–37, 2006.

[49] W.E. Schiesser. *The Numerical Method of Lines: Integration of Partial Differential Equations*. Academic Press, San Diego, 1991.

[50] Dale E Seborg, Duncan A Mellichamp, Thomas F Edgar, and Francis J Doyle III. *Process dynamics and control*. John Wiley & Sons, 2010.

[51] Feng Shang, James G Uber, and Lewis A Rossman. Modeling reaction and transport of multiple species in water distribution systems. *Environmental science & technology*, 42(3):808–814, 2007.

[52] F Greg Shinskey. *Process control systems: application, design and tuning.* McGraw-Hill, Inc., 1990.

[53] Rodney A Stewart, Rachelle Willis, Damien Giurco, Kriengsak Panuwatwanich, and Guillermo Capati. Web-based knowledge management system: linking smart metering to the future of urban water planning. *Australian Planner*, 47(2):66–74, 2010.

[54] Kate McMordie Stoughton, Jennifer Williamson, Brian Boyd, James Cabe, Scott Brown, Douglas Dixon, Susan Loper, Douglas Elliott, Emily Wendel, Marcus De La Rosa, Elisabeth Giever, and Benton Russell. Army net zero: Water balance and roadmap programmatic summary. Pacific Northwest National Laboratory for the United States Army, October 2013.

[55] Ezio Todini. Looped water distribution networks design using a resilience index based heuristic approach. *Urban water*, 2(2):115–122, 2000.

[56] Cara R Touretzky and Michael Baldea. Nonlinear model predictive control of energy-integrated process systems. *Systems & Control Letters*, 62(9):723–731, 2013.

[57] D Trawicki, K Duzinkiewicz, and MA Brdys. optimising model predictive controller for hierarchical control of integrated quality and quantity in drinking water distribution systems. In *IFAC I International Conference on Technology, Automation and Control of Wastewater Systems-TiASWiK'02*, pages 19–21, 2002.

[58] Kalanithy Vairavamoorthy and Mohammed Ali. Optimal design of water distribution systems using genetic algorithms. *Computer-Aided Civil and Infrastructure Engineering*, 15(5):374–382, 2000.

[59] Adam Jacobus Van Staden, Jiangfeng Zhang, and Xiaohua Xia. A model predictive control strategy for load shifting in a water pumping scheme with maximum demand charges. *Applied Energy*, 88(12):4785–4794, 2011.

[60] John J Vasconcelos, Lewis A Rossman, Walter M Grayman, Paul F Boulos, and Robert M Clark. Kinetics of chlorine decay. *American Water Works Association. Journal*, 89(7):54, 1997.

[61] Peter J. Vikesland, Kenan Ozekin, and Richard L. Valentine. Monochloramine decay in model and distribution system waters. *Water Research*, 35(7):1766–1776, 2001.

[62] Godfrey A Walters, Driss Halhal, Dragan Savic, and Driss Ouazar. Improved design of anytown distribution network using structured messy genetic algorithms. *Urban Water*, 1(1):23–38, 1999.

[63] Jingsong Wang and Mietek A Brdys. Optimal operation of water distribution systems under full range of operating scenarios. In *Proceedings of 6th UKACC International Control Conference, Glasgow, paper*, number 112, 2006.

[64] GP Yu, RS Powell, and MJH Sterling. Optimized pump scheduling in water distribution systems. *Journal of optimization theory and applications*, 83(3):463–488, 1994.

Vita

Corey James was born in Freeport, Texas on 18 October 1976. He received a Bachelors of Science degree in Chemistry from the United States Military Academy at West Point in 1999. After attending flight school and becoming an AH-64D Apache aviator, he served in Germany, Iraq, Kuwait, and Texas before returning to graduate school and receiving his M.S. in Chemical Engineering from the University of Texas in 2009. He served on the faculty at West Point from 2009 to 2012 where he was selected as a permanent, or "Academy", professor. While serving again in Germany and one last combat tour to Afghanistan in 2012, Corey applied to the Ph.D. program in Chemical Engineering at the University of Texas at Austin. He was accepted and started graduate studies under the supervision of Dr. Thomas F. Edgar and Dr. Michael E. Webber in August 2014. Corey is married to the former Jo-Reed McDougal and has two sons, Caleb and Colton. He will spend the remainder of his military service as an Academy Professor of chemical engineering at West Point.

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